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Understanding grassland dynamics in the steppe zone of Kazakhstan – a remote sensing analysis

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Abstract

Temperate grasslands are widespread, provide important ecosystem services, and often offer good conditions for agriculture. As a result, many temperate grasslands are undergoing agricultural land-use change. While in most world regions these changes result in expansion and intensification of agriculture, some regions exhibit the opposite trajectory, providing opportunities for balancing trade-offs between food production and grassland restoration. Land abandonment may lead to negative ecological consequences, though, such as increasing fire frequency or severity.

The temperate steppes of Kazakhstan are one of the world regions that experienced massive changes in land management intensity and widespread land-use change after the breakdown of the Soviet Union. Cropping and grazing regime changes across the steppes of Kazakhstan are understudied, and related spatio-temporal changes, e.g. in fire regimes, are still poorly understood. The main research goal of this thesis was accordingly to develop a methodology to map related change at appropriate scales and to provide novel datasets with high spatial and temporal detail to enhance our understanding of how the coupled human-environment in Northern Kazakhstan has changed since the 1980s. An approach was developed to identify the timing of post-Soviet cropland abandonment and recultivation in northern Kazakhstan based on annual Landsat time series. Knowing the timing of abandonment allowed for deeper insights into what drives these dynamics: for example, recultivation after 2007 happened mainly on land that had been abandoned latest. Likewise, knowing the timing of abandonment allowed for substantially more precise estimates of soil organic carbon sequestration. Mapping changes in fire regimes (i.e. extent, number and size of fires) highlighted a sevenfold increase in burnt area and an eightfold increase in number of fires after the breakdown of the Soviet Union. Agricultural burning as well as cropland and pasture abandonment were associated with increased fire risk. It was therefore important to provide better estimates on how grazing pressure changed after the dissolution of the Soviet Union. Grazing probabilities, derived from a number of spectral indices using a random forest, were found to provide the best metrics to capture grazing pressure. The analysis revealed a general decline in grazing pressure in the Kazakh steppe after 1992. The effect was mostly pronounced near abandoned livestock stations, and significantly increased with distance from such points. Collectively, the analyses in this dissertation highlight how dense records of Landsat images can be utilized to better understand land use changes and the ecology of steppes across large areas. The datasets developed within this thesis specifically allow to disentangle the processes leading to and the impacts of agricultural abandonment in the temperate Kazakh steppes, and may potentially be used to support decision-making in land-use and conservation planning.

Zusammenfassung

Graslandflächen sind in den gemäßigten Breiten weit verbreitet; sie leisten wertvolle Ökosystemdienstleistungen und sind wichtig für die Landwirtschaft. In vielen Weltregionen findet auf Graslandflächen ein Landnutzungswandel statt, der mit landwirtschaftlicher In- und Extensivierung einhergeht. In manchen Gebieten kann jedoch auch die Aufgabe der landwirtschaftlichen Bewirtschaftung beobachtet werden. Landaufgabe wird häufig zuerst mit negativen Konsequenzen, wie z.B. einer steigenden Anzahl von Feuern verbunden, bietet aber auch die Möglichkeit, Kompromisse zwischen der Nahrungsmittelproduktion und der Wiederherstellung von Graslandflächen zu finden. Die Steppen in Kasachstan gehören zu den Regionen, in denen es nach dem Zusammenbruch der Sowjetunion sowohl zu einem großflächigen Landnutzungswandel, als auch zu massiven Änderungen der Nutzungsintensität kam. Diese Veränderungen der Acker- und Weidenutzung - und die damit verbundenen räumlichen und zeitlichen Dynamiken des Feuerregimes (d.h. Ausmaß, Anzahl und Größe der Brände) - sind noch nicht ausreichend verstanden. Daher war das Hauptforschungsziel dieser Dissertation, eine Methode zu entwickeln, die es ermöglicht die beschriebenen Veränderungen in einem adäquaten Maßstab zu kartieren. Es wurden Datensätze mit hoher räumlicher und zeitlicher Auflösung erstellt, mit denen die Veränderungen im Mensch-Umweltsystem des nördlichen Kasachstans seit den 1980er Jahren analysiert werden konnten. Ein auf jährlichen Landsat-Zeitreihen basierender Ansatz wurde entwickelt, um die Zeitpunkte der Aufgabe und Rekultivierung von landwirtschaftlichen Flächen zu identifizieren und Landnutzungsdynamiken zu verstehen. Die Zeitpunkte der Landaufgabe ermöglichten z.B. die Schätzung der organischen Kohlenstoffbindung im Boden. Weiterhin ermöglichten die Zeitpunkte der Landaufgabe die Schätzungen der organischen Kohlenstoffbindung im Boden. Eine Kartierung der Änderungen im Feuerregime zeigte eine siebenfache Zunahme an verbrannter Fläche und eine Verachtfachung von Bränden nach dem Ende der Sowjetunion. Da sowohl landwirtschaftliche Feuer, als auch die Landaufgabe mit einem erhöhten Brandrisiko assoziiert werden konnten, wurde mit Spektralindizes und einem Random Forest Modell quantifiziert, wie sich der Beweidungsdruck nach dem Zerfall der Sowjetunion verändert hat. Die Analyse ergab einen Rückgang des Beweidungsdrucks in der kasachischen Steppe nach 1992, wobei dieser Effekt meist in der Nähe von aufgegebenen Nutzviehhaltestationen auftrat und mit größerer Entfernung abnahm. In dieser Dissertation konnte gezeigt werden, wie Landsat-Zeitreihen genutzt werden können, um großflächige Landnutzungsänderungen und die Ökologie von Steppen besser zu verstehen. Die entwickelten Datensätze ermöglichen es, die Prozesse, die zur Landaufgabe und den damit zusammenhängenden Auswirkungen auf die kasachische Steppe führten, zu entwirren und können zur Entscheidungsfindung in der Landnutzungs- und Naturschutzplanung verwendet werden.

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Introduction

1 Background

1.1 Grasslands and land-use change

Grasslands are usually defined by their predominantly herbaceous and short shrub vegetation and have a climate that is favorable for this kind of vegetation, but does not allow woodlands to develop (Whittaker and Likens, 1975; White et al., 2000). Assessment of grassland extent on the planetary scale vary widely in different sources, though it is commonly estimated to be between 31 and 43 percent of the global area (White et al., 2000), which makes them the largest global biome (Lieth, 1978). Grasslands are rich in biodiversity (Suttie et al., 2005), including many endemic plant species and charismatic large mammals (Milner-Gulland et al., 2001). For example, the predecessors of important species for humanity, such as wheat and horse, take their origins in grassland biomes (Colledge et al., 2007; Levine, 1999). These ecosystems play a globally important role as carbon storage (Scurlock and Hall, 1998a), containing about 30 % of the global carbon stored in soils (Anderson, 1991). Yet, especially temperate grasslands have been converted on a large scale to agriculture, with about 65 % of its native cover lost (Millennium Ecosystem Assessment, 2005). While this increases agricultural production, the resulting environmental tradeoffs (e.g., soil degradation, carbon emissions, sinking water tables, biodiversity loss) can be stark (Foley, 2005; E. F. Lambin and Meyfroidt, 2011; Meyfroidt et al., 2016). Understanding where and why grassland conversions happen is therefore important.

Given the challenge to feed almost 10 billion people in the next decades (United Nations, Department of Economic and Social Affairs, Population Division, 2015), the intensification of agriculture, both in terms of cropping and grazing systems, seems unavoidable and could be less environmentally costly than converting more natural areas (Foley, 2005; E. F. Lambin and Meyfroidt, 2011). Identifying pathways to intensify agricultural systems while minimizing the environmental costs of intensification has therefore become a key research issue in land use and conservation science (Foley et al., 2011; E. F. Lambin and Meyfroidt, 2011). A prerequisite in this context are approaches and datasets that allow to monitor management intensity across larger areas.

This is particularly important for livestock systems. Livestock and milk production are key land-use activities in grasslands. The spatial allocation of grazing pressure also plays a crucial role for how grazing affects grassland ecosystems. For example, 16 % of the world's pastures are suffering from degradation (FAO, 2010), often caused by overgrazing (Hilker et al., 2014; Wang et al., 2014). In turn, low grazing pressure can change vegetation structure and composition, as some species are dependent on grazing, and can negatively affect carbon sequestration (Follett et al., 2001).

Another possible consequence of low grazing intensity is an alteration of fire regime, as fire is an important feature of grassland systems (Fuhlendorf et al., 2009; Keeley and McGinnis, 2007; Smelyanskiy et al., 2015). Low grazing intensity leads to an accumulation of litter in grasslands, which may increase the frequency as well as the temperature of wildfires (Smelyanskiy et al., 2015). Some grass species are fire dependent, and fires often define vegetation succession in grasslands, which in turn strongly influences biodiversity at all trophic levels (Pyne, 1984). Grazing and cropping can change fire dynamics markedly. For example, well-balanced grazing could reduce fire rates and mitigate their negative consequences (Fuhlendorf and Engle, 2004). Cropland and grazing abandonment, in contrast, can increase fire rates (Fuhlendorf et al., 2009; Moreira and Pe'er, 2018). On the other hand, prescribed burning of agricultural land in some regions substantially contribute to global air pollution, as well as to global warming (McCarty et al., 2017; Smelyanskiy et al., 2015; Stohl et al., 2007). Thus, it is important to understand fire regimes in grassland ecosystems, as well as interactions between land use and fire regimes.

While in most places intensification or expansion of agriculture uses occur, in other places agricultural abandonment, driven for example by regime shifts, may take place (Baumann et al., 2011; Griffiths et al., 2013a; Eric F. Lambin and Meyfroidt, 2011). One of these areas is the Eurasian steppe, where abandonment of croplands and pastures happened on an unprecedented scale after the collapse of the Soviet Union (Alcantara et al., 2013; Prishchepov et al., 2012a). Two main agricultural activities in that region are wheat production and livestock breeding. Both had a moderate to high intensity in Soviet era, but after its breakdown, subsidies into the agricultural sector diminished, the inner market collapsed, and rural outmigration started resulting in shrinkage of the area under cereal production, reduced input of fertilizers, and the decay of machinery and grazing infrastructure (Prishchepov et al., 2013, 2012a; Swinnen et al., 2017). Agricultural abandonment have led to both positive and negative ecological consequences. On the one hand, it provided an opportunity for natural steppe restoration and carbon sequestration (Brinkert et al., 2016; Kurganova et al., 2014; Schierhorn et al., 2013). On the other hand, it resulted in accumulation of dry litter, which together with the general chaos accompanying transition to the market economy could have resulted in the intensification of fire regimes (Dubinin et al., 2011, 2010). However, the most direct consequences of these land-use conversions were a dramatic drop in food production and life quality in rural areas (Swinnen et al., 2017). Novel datasets that could reveal spatial and temporal details of agricultural abandonment and its consequences are needed in order to assess the aforementioned effects and to plan measures to efficiently manage the processes of steppe restoration.

The role of global meat production

Previous research suggests that steppe and semi-desert areas of Eurasia have a large potential in sustainable livestock breeding (Eisfelder et al., 2014; B. R. Hankerson et al., 2019; Kraemer et al., 2015), which could foster natural steppe restoration and mitigate some of the negative consequences of agricultural abandonment, such as increased fire rates and severity (Brinkert et al., 2016; Dubinin et al., 2011). Furthermore, following the decrease in supply in the world's meat market after the collapse of the Soviet Union and its livestock sector, the livestock numbers in other countries could have increased in order to fulfill the demand (E. F. Lambin and Meyfroidt, 2011). Africa and Latin America are highlighted as both hotspots of biodiversity and regions of expanding and intensifying agricultural production, making them particularly vulnerable to an increase in meat production (Kehoe et al., 2015; Kreidenweis et al., 2018). Some vivid examples of a rise in livestock numbers in Latin America in the 1990s are Brazil, Mexico, and Paraguay (Figure I-1), where increasing meat production is frequently either directly or indirectly linked to deforestation (Henders et al., 2015; Machovina et al., 2015; Schierhorn et al., 2016). Moreover, a substantial part of meat produced in Brazil is exported to Russia (Kaimowitz et al., 2004; Schierhorn et al., 2016), the region with the largest areas of grasslands globally (White et al., 2000). In this regard, reviving the livestock sector in grassland regions could be less environmentally harmful than intensifying meat production in the tropics. This is particularly so for the Eurasian steppes, as land-use intensity and biodiversity in such regions as South-American Pampas is substantially higher (Kehoe et al., 2015). Given the need to increase food production to feed a growing global population, a better land-use management of low competition lands could be a relatively sustainable tradeoff (E. F. Lambin and Meyfroidt, 2011). However, reviving livestock numbers needs thorough planning in order to achieve these goals with minimal negative consequences for grassland ecosystems. Spatially explicit and detailed datasets of historical and current cropland extent, grazing pressure, and fire hotspots are, therefore, of a paramount importance.

Most of the research was previously conducted on the North American prairies, leaving the Eurasian steppes significantly understudied. Consequently, data for this region are either missing or lacking spatial and temporal details. Statistical data is frequently also missing, or is unreliable due to frequent misreporting (Burkitbayeva and Oshakbayev, 2015; Kraemer et al., 2015). Therefore, remote sensing is one of the most reliable sources of information for this area.

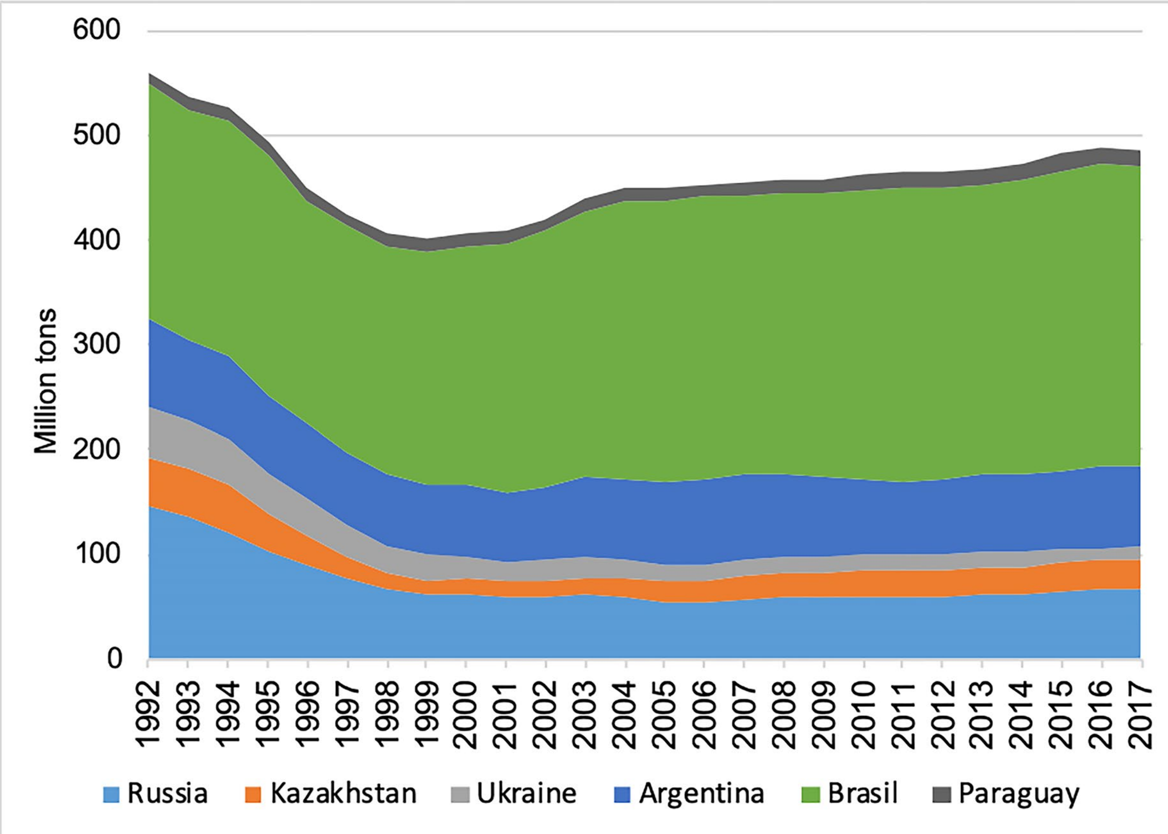

Figure I-1: Beef production dynamics in the selected forest-dominated (Argentina, Brazil, and Paraguay) vs. grassland-dominated (Russia, Ukraine, and Kazakhstan) countries in 1992-2017, FAOSTAT.

1.2 Kazakh steppes as a study region

Grasslands cover a substantial part of the terrestrial land (White et al., 2000). One of the largest continuous grassland areas on Earth is the Eurasian steppe belt, which stretches from Bulgaria to Manchuria. This area was a cradle to many nomadic civilizations, and was used for a transhumance livestock grazing for millennia (Kalieva and Logvin, 2011).

Most of the steppes are still used for livestock production. Nowadays much of this area is ploughed as well (Lioubimtseva and Henebry, 2012; Kraemer et al., 2015). As most of Eurasian steppe belt lies within former Eastern Bloc-countries, significant land-use changes happened in the in the region in the 1990s following the breakdown of the Soviet Union, mostly involving agricultural abandonment (Alcantara et al., 2013; Prishchepov et al., 2013). A substantial part of the Eurasian steppe is located in the northern part of Kazakhstan.

Northern Kazakhstan is an interesting study region for a number of reasons. First, land-use changes of an unprecedented scale happened in that region during and after the Soviet period, potentially affecting other parts of the world, as has been outlined above (de Beurs and Henebry, 2004; Kraemer et al., 2015). Second, this area was largely understudied partly due to the existing gaps in satellite archives (Kovalskyy and Roy, 2013). Third, frequent and extensive fires in the area affect local as well as global environments (Loboda et al., 2012; McCarty et al., 2017; Smelyanskiy et al., 2015). Novel datasets and understanding the drivers of fire regimes are therefore of a paramount importance. Finally, the local government is seeking to intensify crop production and to revive livestock numbers, as well as wild ungulate populations in the region (Ministry of Agriculture of the Republic of Kazakhstan, 2018; Nazarbayev, 2010), which requires datasets to facilitate managerial decisions in these regards.

The steppe zone is the most important agricultural region of Kazakhstan, making the country one of the biggest wheat producers globally (FAO, 2014), with more than 11 million ha cultivated in 2015 (*Results of spring sowing campaign in 2015*, 2015). Kazakhstan today also has one of the world's largest areas of permanent meadows and pastures (FAO, 2014). Yet, the region has a long land-use history. Historically large charismatic ungulates such as saiga antelope (*Saiga tatarica*) (Singh and Milner-Gulland, 2011), Kulan (*Equus hemionus kulan*), Przewalski horse (*Equus ferus przewalskii*) (Bahloul et al., 2001), and Siberian roe deer (*Capreolus pygargus*) roamed the steppes of Kazakhstan. By the 19th century the numbers of wild ungulates drastically decreased due to hunting (Robinson and Milner-Gulland, 2003). Nomadic peoples inhabited the steppes for millennia, herding their livestock using a transhumance system of summer ("Zhaylau" in Kazakh, or "Letovkas" in Russian) and winter ("Kystau" in Kazakh, or "Zimovkas" in Russian) pastures. They used either northern, or mountain steppes that are rich in biomass, have more water resources and are generally cooler in summer; and deserts and desert steppes that have less snow cover, more shrub vegetation, and are generally warmer in winter. Portable tents ("yurts") construction allowed for easy migration, and the exact place of camping was frequently defined by the fodder quality and quantity. This system allowed redistributing grazing pressure on steppe, while maximizing fodder availability for livestock (Kerven et al., 2006). Due to a low number of sedentary settlements in the region, crop cultivation was negligible in Kazakhstan before the 19th century when the Russian settlers moved to the northern and eastern regions of Kazakhstan. However, the increase in cultivated area was still low.

The dramatic changes began with the rise of the Soviet Union. First, the collectivization program enforced by the Soviet government in 1929 involved livestock confiscation from nomadic herders and individual farmers in order to establish collective farms. The latter had neither capacity nor feed to maintain large amounts of livestock (Olcott, 1981). In addition, many herders butchered their livestock rather than giving it away. These caused an approximately tenfold decrease in livestock numbers in Kazakhstan and a subsequent famine that took away lives of approximately 1.4 million people, or more than 30 % of the population at that time (Pianciola, 2001). Second, most of the northern part of steppe was allocated for wheat production in 1954 during Khrushchev's Virgin Lands campaign (McCauley, 1976a). The most fertile *Chernozem* (black soil) rich areas were ploughed first followed by the less productive *Castanozem* (chestnut soil) areas. The remaining grasslands were used for intensification of the livestock sector. By that time Soviet agronomists adopted some practices from the local nomads, for example using winter and summer livestock stations to simulate seasonal migration. Nevertheless, the movements were limited by infrastructure and machinery, and the livestock numbers were higher, while the area designated for grazing was smaller than in pre-Soviet times (Kerven et al., 2006). As hunting was controlled by the government, the saiga population also partly recovered. Due to high livestock numbers, grassland degradation possibly took place in parts of the Eurasian steppe (Robinson et al., 2003).

After the breakdown of the Soviet Union in 1990, the area of croplands in the region contracted by approximately 30 %, and the livestock sector collapsed in Kazakhstan with the sheep numbers dropping almost as deep as the level of collectivization time, although without the same catastrophic consequences (Kamp et al., 2011). In spite of the large scale of these changes, information of the exact spatial extent as well as timing of cropland abandonment have been missing so far. Decrease in livestock numbers could result in a drastic decline of a grazing pressure on most of the grasslands. At the same time the remaining livestock was concentrated in the villages all year around, due to the lack of machinery and collapsed infrastructure, likely causing overgrazing of these areas (Alimaev et al., 2008). However, neither the spatial patterns nor magnitude of these changes have been mapped. The increase in fuel availability together with decreased control and fire suppression capabilities most probably resulted in the intensification of fire regimes (Brinkert et al., 2016; Dubinin et al., 2011). No study has compared fire regimes in northern Kazakhstan before and after the collapse of the Soviet Union, nor have the links between possible intensification of fire regimes and land-use change been studied. However, the region is frequently marked as a global fire hotspot (Archibald et al., 2013; Giglio et al., 2013), and traces of fires from this area were found as far as in Alaska (Warneke et al., 2009).

The population of saiga antelopes also decreased dramatically in the 1990s due to the increased poaching as a result of the lack of governmental control (Milner-Gulland et al., 2001) followed by a mass die-off in 2015 (Kock and Robinson, 2019). The government of Kazakhstan has started cropland recultivation and revival of livestock sector as early as the beginning of the 2000s (Meyfroidt et al., 2016; Ministry of Agriculture of the Republic of Kazakhstan, 2018). Restoring saiga populations as well as reintroducing kulans in the steppe of Kazakhstan are the official goals of the government (Ministry of Agriculture of the Republic of Kazakhstan, 2018). Both revival of agricultural sector and conservation programmes require adequate datasets for an effective decision making.

1.3 Mapping land-use change-related processes in steppes

Remote sensing allows for studying land-cover and land-use change at high spatial and temporal resolution (Kuemmerle et al., 2013; Lambin and Geist, 2006), overcoming problems inherent to aggregated statistical data (Prishchepov et al., 2012a). In addition, agricultural statistics cannot serve as a reliable source of information in ex-Soviet countries due to data quality issues (Burkitbayeva and Oshakbayev, 2015). One prerequisite of studying land-use changes followed the breakdown of the Soviet Union is a temporal depth of an imagery archive. The Landsat program, started in 1972, provides particularly interesting opportunities for advancing historical land-cover and-use mapping (Fritz et al., 2013, 2011). Since the launch of Landsat 5, equipped with 30 m Thematic Mapper (TM) sensor in 1984, continuous fine-scale observation became possible. Despite the observation gaps in the 1990s, it is possible to use the entire depth of the Landsat archive e.g., using multi-temporal spectral-statistical metrics (Griffiths et al., 2013b; Pflugmacher et al., 2019)

A number of studies on cropland abandonment in Post-Soviet countries exist (Baumann et al., 2011; de Beurs and Ioffe, 2014; Prishchepov et al., 2013), but most of those studies used coarse-resolution data. Estel *et al.* (2015) mapped cropland abandonment and recultivation across Europe using MODIS NDVI time series. Another study in Central and Eastern Europe provided a map of cropland and pasture abandonment (Alcantara et al., 2013). However, MODIS data is coarse and some agricultural fields are smaller than the MODIS pixel size. Further, the sensor was launched in 1999 thus not providing a baseline from Soviet times. Griffiths et al. (2013a) found a widespread agricultural abandonment while mapping post-Soviet land-use conversions in Romania using Landsat imagery. One of the few fine-scale studies that include the Kazakh steppe was performed by Kraemer *et al.* (2015) who studied cropland abandonment in Kostanay region of Kazakhstan. The study found that most of the abandoned agricultural area is located in areas with relatively low crop production potential. However, this work only covered discrete time steps (three years). While these studies highlight the potential for mapping abandonment and recultivation, no study has done so using the full Landsat record back to 1984.

Fire is an important driver of grassland change, but mapping active fire in grasslands is hard because of the comparatively low burning temperature (Schroeder et al., 2008) due to the limited fuel load (Hantson et al., 2013). Furthermore, fire propagates very quickly across grasslands, sometimes at speeds of >50 meter/minute (Smelyanskiy *et al.*, 2015), hence affecting the detectability of active fires by satellites (Boschetti and Roy, 2009; Roy et al., 2008). The fact that ash is typically being blown away and post-fire vegetation may appear as soon as one month after the fire (Arkhipkin et al., 2010) complicates burned-area mapping in steppes as well. Previous studies that mapped burned area in the region relied on coarse resolution imagery, such as MODIS. However, many studies suggest that MODIS omits many smaller fires, e.g., agricultural burnings, in the Eurasian steppes (Hall et al., 2016; Hantson et al., 2013; McCarty et al., 2017). Moreover, MODIS is available only from 1999, which does not allow mapping the Soviet period.

Mapping grazing pressure is a challenging task, because livestock numbers are typically only available for aggregated administrative units and separating grazing impact from the often highly dynamic vegetation phenology is challenging. Developing methods to characterize spatial patterns of grazing is thus important. While satellite imagery is capable of separating grasslands from other land covers reliably using phenological differences (Estel *et al.*, 2015; Heumann *et al.*, 2007; Jamali *et al.*, 2015), no robust methodology exists to map changes in grassland condition in semi-arid regions. Propastin *et al.* (2008)

mapped grasslands across all of Central Asia, highlighting northern Kazakhstan as a hotspot of vegetation change. However, the study did not separate cropland and grassland and it was carried out at very coarse resolution (8 km, AVHRR imagery), making it impossible to detect the fine-scale degradation patterns that are typical for the region. Hilker *et al.* (2014) conducted a study on Mongolian grassland degradation using MODIS time series and Fourier analyses, showing that grassland degradation in the Mongolian steppe was indeed mainly caused by overgrazing. Although MODIS is well suited for analyzing temporal patterns, its spatial resolution remains an issue for fine scale analyses.

A few studies have assessed the usefulness of Landsat imagery. For example, Li et al. (2013) studied grassland desertification using Landsat imagery in China, showing that the grazing ban helped to revert desertification. Lehnert *et al.* (2015) performed a comparison of different sensors and methods to study grassland dynamics in the Tibetan plateau, finding certain methods, such as SVM to map grassland cover reliably. De Beurs *et al.* (2016) developed a grassland disturbance index to study grassland degradation in New Zealand, yielding high accuracy. Karnieli *et al.* (2008) assessed spatial patterns of degradation in the Central Asian desert. These studies highlight the potential to map grassland degradation in northern Kazakhstan using Landsat imagery, yet to my knowledge no such study has done so.

The datasets of cropland abandonment and recultivation, the maps of grazing pressure and fire regime change, as well as the insights on drivers, consequences, and interactions of these changes are all urgently needed to facilitate decision-making processes in agricultural and fire management as well as in conservation planning.

2 Conceptual framework

2.1 Research questions and objectives

The overarching goal of this dissertation is to better understand land-use changes and their consequences in the steppes of Kazakhstan triggered by the breakdown of the Soviet Union by (1) developing a novel methodology for mapping subtle changes in land cover and land use in semi-arid steppes with the highest possible spatial and temporal details given scarce data availability, and (2) assessing the links between post-Soviet land-use change and its consequences.

By achieving this goal, the dissertation contributes to an advancement of remote sensing methodology, better understanding land-use change in northern Kazakhstan, understanding the interactions between land-use change and natural processes, and potentially provides important datasets for local policy-makers to restructure land-use infrastructure, to plan restoration and conservation programs, as well as to improve fire management strategies. To achieve these goals, this dissertation addressed two main research questions:

Research Question I: *How to map changes in cropland and burned area extent as well as in grazing pressure in a steppe ecosystem given scarce data?*

Previous studies suggest that massive cropland abandonment and their partial recultivation thereafter, together with a drastic decrease in livestock number, happened in northern Kazakhstan. This could have led to an intensification of fire regimes in the area. However, existing datasets are either missing, or lacking spatial and temporal details. Previous attempts to map changes in cropland extent and grazing pressure in the region relied either on low-resolution imagery, thus lacking spatial details, or snapshots in time, thus omitting inter-annual variations. This was partly due to the data gaps and a lack of methodological framework for a sound and robust time-series analysis. Recent developments in such approaches as image compositing, class membership probability mapping, as well as trajectory-based analysis (e.g., LandTrendr) allow to overcome these limitations.

Research Question II: *What was the environmental impact of post-Soviet land-use change on the steppes of Kazakhstan?*

Land-use changes may have far-reaching negative as well as positive consequences. Given that the detailed datasets of land-use and burned area change for the northern Kazakhstan were missing, it was not possible to assess changes in fire regimes, and their relation to land-use change in Kazakhstan. Similarly, without knowing the exact timing and extent of cropland abandonment and recultivation, estimates of soil organic carbon stored after the abandonment would be highly unreliable. The datasets from the Research Question I facilitated closing these gaps.

Two main objectives were aiming to answer these research questions (Figure I-2):

Objective 1. Develop a methodology to map changes in cropland and burned area extent as well as in grazing pressure in steppe ecosystem given scarce data.

Recent advancements in remote sensing techniques provide an opportunity to overcome the limitations that previously prevented fine-scale mapping of cropland conversions and grazing pressure changes in semi-arid steppes. This allows mapping cropland abandonment and recultivation, burned area, grazing pressure, and their changes from the late Soviet period through the time of lowest agricultural intensity until now.

Objective 2. Assess the environmental impact of post-soviet land-use change.

The maps from the Objective 1 provide insights on the forces driving the land-use change and fire regime change in northern Kazakhstan. Maps of cropland abandonment and recultivation timing allow estimating soil organic carbon sequestration more precisely.

Altogether, the methodology, the datasets, and the conclusions provided in this dissertation may be potentially used by local authorities for sustainable and effective management of livestock revival program, improving the fire management policies, and planning conservation and restoration programs.

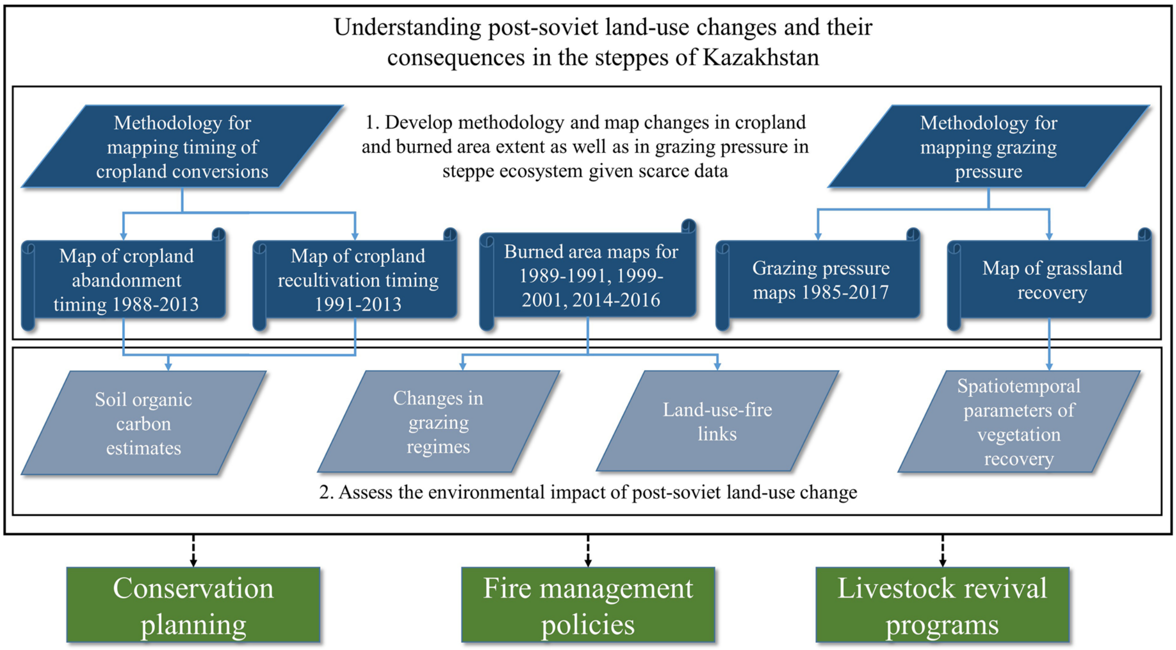

Figure I-2: A conceptual framework of the dissertation that describes the major outcomes (in blue tones) grouped by objectives they belong to. Altogether, they are facilitating achievement of the overarching goal, which in turn may be potentially used for improvement of decision-making by local authorities (in green).

2.2 Structure of this thesis

This thesis consists of five chapters: The Introduction (Chapter I) is followed by three core research chapters (Chapters II-IV) that contribute to answering the research questions outlined above, and a Synthesis chapter (Chapter V) that provides a summary of the core chapters, demonstrates interconnection between them, and provides an outlook for potential research. Appendix A provides an example of such an application of the datasets for solving problems in nature conservation. The three research chapters and the appendix (see list below) were written as stand-alone manuscripts and either published in or submitted to international, peer-reviewed journals. Since each research chapter needed to meet the required structure for journal articles, a thematic overlap between chapters has to be accounted for.

Chapter II ***Dara, A.***, *Baumann, M., Kuemmerle, T., Pflugmacher, D., Rabe, A., Griffiths, P., Hölzel, N., Kamp, J., Freitag, M., Hostert, P. (2018). Mapping the timing of cropland abandonment and recultivation in northern Kazakhstan using annual Landsat time series. Remote Sensing of Environment, 213, 49-60.*

This chapter provides a novel methodology for mapping changes in cropland extent in northern Kazakhstan using the entire depth of the Landsat archive, class membership probabilities, and time-series analysis. The results include the maps of cropland abandonment between 1988 and 2013, and recultivation between 1991 and 2013. The study provides insights on the effect of scarce observation periods on the accuracy of time series analysis. Spatially and temporally detailed maps of a fallow period duration before recultivation allowed calculating substantially more precise estimates of soil organic carbon sequestered in the area.

Chapter III ***Dara, A.***, *Baumann, M., Hölzel, N., Hostert, P., Kamp, J., Mueller, D., Ullrich, B., Kuemmerle, T. (2019). Post-Soviet land-use change affected fire regimes on the Eurasian steppes. Ecosystems.*

This chapter reveals the changes in fire regimes in northern Kazakhstan by providing fine-resolution burned area maps for the soviet period (1989-1991), the period of lowest agricultural activity (1999-2001), and a recent period (2014-2016). Land cover and land-use maps from the Appendix A combined with screen-digitized livestock husbandry stations and settlements help to establish strong links between the post-Soviet land-use change and changes in fire regimes.

Chapter IV *__Dara, A.__, Baumann, M., Freitag, M., Hölzel, N., Hostert, P., Kamp, J., Mueller, D., Prishchepov, A., Ullrich, B., Kuemmerle, T. (2020). Annual Landsat time series reveal post-Soviet changes in grazing pressure. Remote Sensing of Environment, 239, 111667.*

This chapter evaluates a number of Landsat-based spectral metrics in their ability to capture grazing pressure change using a random forest classifier and field-collected vegetation plots including the number of dung piles and biomass yield. Robustness of the resulting grazing class probabilities as a grazing pressure metric over time was assessed using the screen-digitized livestock husbandry stations and settlements. Trajectory-based analyses of annual grazing pressure maps provide a quantitative assessment of changes in grassland condition due to changes in grazing pressure over the Kazakh steppe from 1985 to 2017.

Appendix A *Baumann, M., Bleyhl, B.,* **Dara, A.**, *Hölzel, N., Kamp, J., Krämer, R., Mueller, D., Pötzschner, F., Prishchepov, A., Schierhorn, F., Urazaliev, R., Kuemmerle, T. (In review). Declining human pressure and opportunities for rewilding in the steppes of Eurasia. Diversity and Distributions*

This chapter provides an example of how spatially and temporally detailed land cover and land-use datasets can be used for the purposes of nature conservation. Landsat-based land cover and land-use maps together with the screen-digitized livestock husbandry stations and settlements were used to show where reduced human pressure led to a restoration of substantial parts of the Kazakh steppe and to improved connectivity between these parts.

Chapter II:
Mapping the timing of cropland abandonment and recultivation in northern Kazakhstan using annual Landsat time series

Remote Sensing of Environment, 2018, Volume 213, Pages 49-60.

Andrey Dara, Matthias Baumann, Tobias Kuemmerle, Dirk Pflugmacher, Andreas Rabe, Patrick Griffiths, Norbert Hölzel, Johannes Kamp, Martin Freitag, and Patrick Hostert

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Abstract

Much of the world's temperate grasslands have been converted to croplands, yet these trends can reverse in some regions. This is the case for the steppes of northern Kazakhstan, where the breakdown of the Soviet Union led to widespread cropland abandonment, creating restoration opportunities. Understanding when abandonment happened and whether it persists is important for making use of these opportunities. We developed a trajectory-based change detection approach to identify cropland abandonment between 1988 and 2013 and recultivation between 1991 and 2013. Our approach is based on annual time series of cropland probabilities derived from Landsat imagery and resulted in reliable maps (89 % overall accuracy), with abandonment being detected more accurately (user's accuracy of 93 %) than recultivation (73%). Most of the remaining uncertainty in our maps was due to low image availability during the mid-1990s, leading to abandonment in the 1990s sometimes only being detected in the 2000s. Our results suggest that of the ~4.7 million ha of cropland in our study area in 1985, roughly 40 % had been abandoned by 2013. Knowing the timing of abandonment allowed for deeper insights into what drives these dynamics: recultivation after 2007 happened preferentially on those lands that had been abandoned most recently, suggesting that the most productive croplands were abandoned last and recultivated first. Likewise, knowing the timing of abandonment allowed for more precise estimates of the environmental impacts of abandonment (e.g., soil organic carbon sequestration estimated at 16.3 Mt C compared to 24.0 Mt C when assuming all abandonment happened right after the breakdown of the Soviet Union, with the uncertainty around emission estimates decreasing by 63 %). Overall, our study emphasizes the value of the Landsat archive for understanding agricultural land-use dynamics, and the opportunities of trajectory-based approaches for mapping these dynamics.

1 Introduction

Grasslands cover about one fifth of the Earth's surface (Lieth, 1978), are rich in biodiversity (Suttie et al., 2005), and play an important role in global carbon storage (Scurlock and Hall, 1998a); (Anderson, 1991). At the same time, grasslands are often found on soils that are well-suited for agriculture (Millennium Ecosystem Assessment, 2005) and can be plowed at comparably low costs (Briggs et al., 2008). However, in some grassland regions croplands are abandoned, potentially leading to a restoration of native biodiversity (Benayas et al., 2007; Brinkert et al., 2016; Kamp et al., 2011) and carbon stocks (Kurganova et al., 2014; Sala et al., 1996). The degree of restoration, however, depends on the time since abandonment, and recovery often follows a non-linear trajectory. For example, carbon sequestration rates were estimated to be significantly lower for croplands abandoned at an earlier date than for more recently abandoned fields in Russia (Kurganova et al., 2014; Wertebach et al., 2017). Similarly, success in restoration of native grass species and a restitution of soil properties were highly dependent on the time since abandonment in China (Zhao et al., 2005). Given recent trends to recultivate some abandoned croplands (Meyfroidt et al., 2016; Schierhorn et al., 2014; Smaliychuk et al., 2016), better information on when croplands were abandoned is important.

The Eurasian steppe belt is an example of a grassland region that has experienced widespread cropland abandonment, starting in the 1980s. Much of the Eurasian steppe belt is located in the former Soviet Union, and a major share of this region was plowed and converted into croplands during the Soviet Virgin Land Campaign (McCauley, 1976b). While the region continues to be one of the world's major bread baskets (Swinnen et al., 2017), it experienced substantial cropland abandonment after the breakdown of the Soviet Union (Baydildina et al., 2000; Schierhorn et al., 2013). This may create an opportunity for mitigating environmental impacts of pre-abandonment land uses and restoring steppe ecosystems (Gerla et al., 2012), as biodiversity and soil carbon stocks can recover with adequate grazing levels and fire regimes (Benayas et al., 2007; Brinkert et al., 2016; Kamp et al., 2011); (Kurganova et al., 2014; Sala et al., 1996). Yet, it takes time for soil and vegetation to fully recover, and while both depend on many factors, previous land use is a key factor (Wright et al., 2012). Identifying those areas that have recovered most, and that might be most valuable from a conservation perspective, depends on understanding land abandonment trajectories. However, reliable data of the exact timing of cropland abandonment in this vast region does not exist.

Remote sensing can play a key role in mapping the extent of cropland abandonment, for example in Eastern Europe (Alcantara et al., 2013; de Beurs and Ioffe, 2014; Estel et al., 2015; Prishchepov et al., 2012a), the African Sahel (Tong et al., 2017; Leroux et al., 2017), and in Central Asia (de Beurs et al., 2015; de Beurs and Henebry, 2004). Most studies that have focused on large areas have relied on coarser resolution data, mainly from the Moderate Resolution Imaging Spectroradiometer (Alcantara et al., 2013; Estel et al., 2015; Yin et al., 2014). While MODIS data provide the high temporal resolution needed to monitor gradual processes such as post-abandonment recovery, MODIS and similar sensors (e.g., VIIRS) lack the temporal depth to assess agricultural abandonment trends in the post-Soviet era of the 1990s. Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) data has a higher spatial resolution and the long temporal record, reaching back into the 1980s, allowing to characterize land use since late Soviet times. However,, existing Landsat-based work in the Eurasian steppe belt has relied on snapshots in time and generally lacked the temporal density to detect the exact timing of abandonment and recultivation (Kraemer et al., 2015), (Baumann et al., 2011; Prishchepov et al., 2013). For example, cropland systems in Eurasia’s steppes are often characterized by a few years of cultivation followed by one fallow year. Thus, studies relying on a few snapshots in time, as in (Kraemer et al., 2015), may therefore confuse fallow periods with abandonment, or miss abandonment phases altogether if areas are put back into production after a few years. With the global availability of Landsat time series data (Wulder et al., 2016), there are now opportunities to overcome these issues by mapping cropland abandonment and recultivation at annual intervals.

Mapping cropland dynamics is challenging because of the high inter- and intra-annual spectral variabilities of cropland (Prishchepov et al., 2012b; Yin et al., 2014). Landsat-based time series approaches can help to overcome these challenges and several such approaches have recently been developed, albeit not with a focus on cropland dynamics. These approaches can be broadly categorized into two groups. The first involves time-series-based classifications of annual land cover (Vogelmann et al., 2009; Zhu, 2017) that captures transitions between land cover classes. The second category of time series approaches fits temporal trajectories to spectral indices for detecting vegetation changes (Forkel and Wutzler, 2015; Kennedy et al., 2010; Verbesselt et al., 2010b), which can detect abrupt breakpoints and continuous trends, but cannot be used if the target class is spectrally highly variable, as is the case with croplands. A useful approach for overcoming these limitations, and making use of the advantages of both groups of time series approaches, is to first predict land-cover probabilities and then use time series of these probabilities as spectral metrics in trajectory-based change algorithms. Such an approach has so far only been applied to MODIS imagery (Yin et al., 2017, 2014) and it remains to be tested whether this approach can be transferred to Landsat time series to map cropland dynamics.

Another challenge for mapping gradual land-use trends with Landsat time series is variable data availability. While some areas, such as the conterminous Unites States or Australia, have a very high availability of Landsat imagery back to the 1980s (Wulder et al., 2016), imagery is scarce for many areas on the globe for at least some periods, often the 1990s (Kovalskyy and Roy, 2013). This is also one of the main challenges in utilizing Landsat imagery for mapping cropland abandonment and recultivation in post-Soviet countries, as data acquisition in the 1990s was often lower, while a majority of abandonment happened in this period. It is thus unclear whether it is possible to detect cropland abandonment and recultivation given such constraints in image availability (Kovalskyy and Roy, 2013; Loveland and Dwyer, 2012).

Our overarching goal therefore was to develop and test a trajectory-based mapping of cropland abandonment and recultivation in Eurasia‘s steppes. Focusing on northern Kazakhstan, we use all available Landsat imagery between 1984 and 2016 to create annual maps of cropland abandonment and recultivation, and to assess the impact of data sparseness on the reliability of our maps. Specifically, we addressed the following research questions:

1. How well do trajectory-based analyses of Landsat time series capture land abandonment and recultivation?
2. How do data-scarce periods affect the accuracy of time series analysis?
3. What is the potential value of more detailed information on abandonment for understanding agricultural dynamics and their environmental impacts?

2 Methods

2.1 Study area

Our study region covers ~79,000 km^2 in the Kostanay Oblast in northern Kazakhstan and considerably smaller border areas of Russia (Figure II-1). The area is interesting from the perspective of methods development for a number of reasons. First, Landsat data availability was scarce in the area during the 1990s. Such a situation is representative for post-Soviet countries and testing the robustness of methods towards data scarcity is therefore important. Secondly, the region is characterized by dynamic and regionally variable patterns of abandonment and recultivation, while at the same time allowing for comparisons with cropland areas that were farmed continuously. Third, the area experienced land-use change patterns typical for the whole region, i.e., cropland abandonment starting in the 1990s and recultivation after 2000 (Meyfroidt et al., 2016). Moreover, we have substantial knowledge of land-use processes in the region, including extensive land-use data useful for ground-truthing from several extensive field trips to the area.

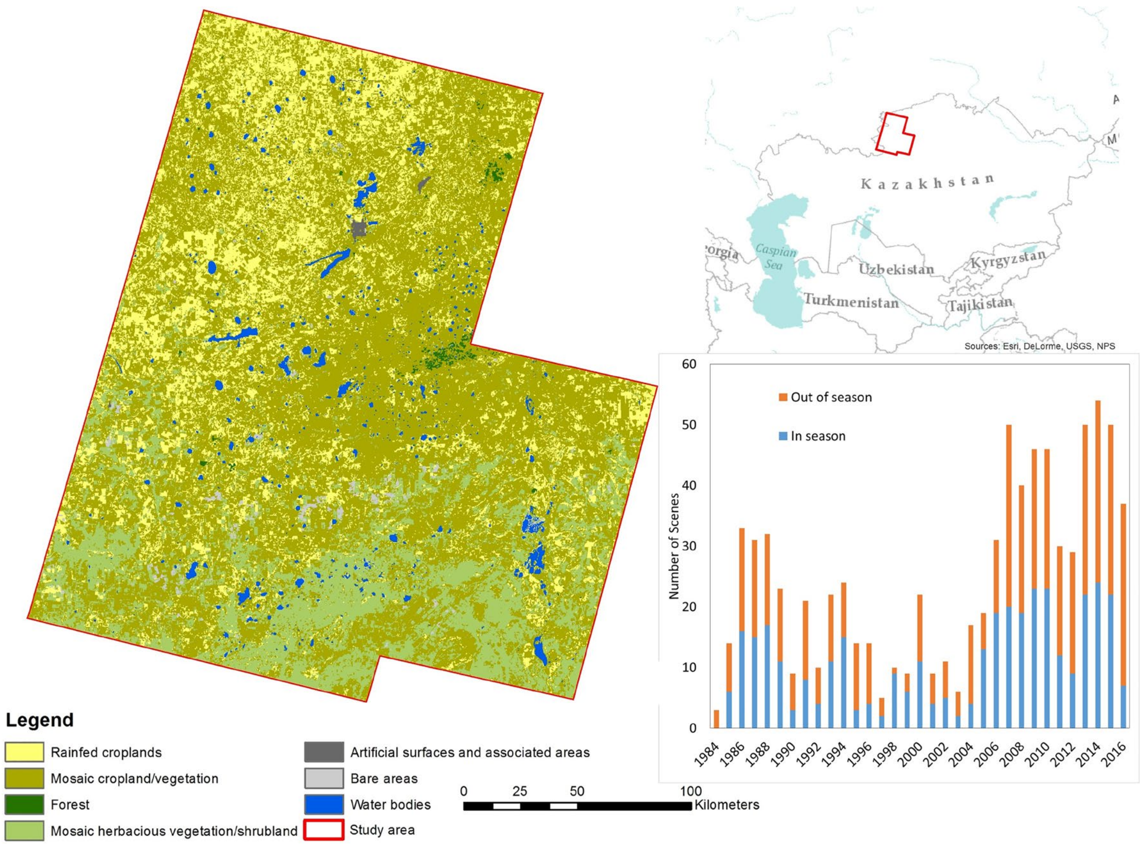

Figure II-1: Study area and data availability. Left: Land cover from GlobCover 2009 (ESA 2010 and UCLouvain). Upper right: Study region in Central Asia. Lower right: Chart of data availability with number of scenes suitable for separating cropland from grassland (in orange: DOY 132 to167 for plowing, and 231 to 294 for harvesting). Landsat data from other DOY in blue.

The terrain in the study region is mostly flat, with elevation ranging between 150 and 300 m above sea level. Climate is continental, with cold and windy winters, followed by hot and dry summers. Annual precipitation varies depending on latitude from 250 to 400 mm. Average monthly temperatures range between -18°C in February and +22°C in July (Ilyakova et al., 2016). These climatic conditions result in a rather short growing season of about 150-180 days (Afonin et al., 2008), and snow cover for approximately 150 days per year (Kauazov et al., 2016). The most common soils are *Chernozems* in the more humid north and *Kastanozems* in the drier southern part of the study area (Beznosov and Uspanov, 1960). Both soil types are generally well-suited for agriculture.

The region has a long land-use history, characterized by nomadic pastoralism for millennia. Cropland cultivation started in the 19th century when Russian settlers started growing wheat crops. Yet substantial cropland expansion happened in the 1950s during Khrushchev's Virgin Lands campaign, when most of the region was plowed, reaching the largest cropland extent in 1963. Neither effects on the environment (Grote, 1997; Josephson et al., 2013), nor severe climatic conditions (Lioubimtseva and Henebry, 2012) were taken into account when converting grasslands to croplands, leading to the abandonment of some areas already during Soviet times. Following the breakdown of the Soviet Union, large wheat cultivation areas were abandoned (Baydildina et al., 2000; Schierhorn et al., 2013). This process was driven by the change from state-controlled to market-oriented economies (de Beurs and Henebry, 2004; Meyfroidt et al., 2016; Prishchepov et al., 2012a), the subsequent decline in agricultural subsidies (Lioubimtseva and Henebry, 2009), and strong rural outmigration (Danzer et al., 2013; Prishchepov et al., 2013). In parallel, livestock numbers dropped dramatically (Robinson and Milner-Gulland, 2003), resulting in a decreasing demand for fodder crops and an associated further contraction of cropland after 1990. Recently, recultivation of abandoned cropland has occurred (Meyfroidt et al., 2016) and governmental programs (Nazarbayev, 2010) seek to revive the livestock sector including through using some of abandoned fields as managed grasslands.

Today, croplands are primarily found in the northern part of the region with its more fertile *Chernozem* soils, whereas livestock grazing is the dominating land use in the drier southern part of our study region. Spring wheat is the historically predominant crop in the region, and only smaller areas are planted with flax, rape, sunflower, and potatoes, however, there has been a tendency to diversify crops in recent years (Ministry of Agriculture of the Republic of Kazakhstan, 2014). The agricultural cycle in the region usually starts with plowing and sowing between mid-May to mid-June. The peak of vegetation growth is in June, and harvesting takes place from late August to late October, depending on weather conditions. Agricultural fields are left fallow for one year once in five to ten years as part of the crop rotation cycle to restore soil water potential. During this fallow year the fields are either being plowed but not sown (so-called "black *par*"), or receive a large amount of herbicides, glyphosate in particular ("chemical *par*"). In recent years, farmers also increasingly use no- or low-till practices. No-till was used on over >1 million ha of cropland in Kazakhstan in 2008 and has increased substantially since 2004 (Kienzler et al., 2012; Derpsch et al., 2010). We describe cropping practices that are most common in the study area. However, the area is considered risky for wheat cropping because of frequent droughts, moreover, not all farmers follow good cropping practices, such as crop rotation.

2.2 Generating annual Landsat time series of spectral variability metrics

We acquired surface reflectance data for three Landsat footprints (WRS-2 paths/rows 161/23, 161/23, and 160/24) for all years between 1984 and 2016 from Landsat TM/ETM+/OLI both from the United States Geological Survey (USGS, 783 scenes) and from the European Space Agency (ESA, 38 scenes) archives (Figure II-1), as the Landsat archive consolidation is still ongoing, and not all ESA scenes are available at the USGS. From the USGS archives, we acquired orthorectified and terrain-corrected (L1T) imagery including cloud and cloud shadow masks based on CFMask (USGS, 2015). Imagery from the ESA archive had to undergo additional geometric correction, as well as cloud and cloud shadow masking. We applied the automated precise registration and orthorectification package (AROP) that resamples all images to a common base image to align the ESA data to the USGS data (Gao et al., 2009). After orthocorrection, we masked clouds and cloud shadows with the Function of Mask (FMask) algorithm (Zhu and Woodcock, 2012), applied the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) for atmospheric correction of Landsat TM and ETM+ imagery (Masek et al., 2006), and followed (Vermote et al., 2016) to correct the OLI images.

We considered images between day of year (DOY) 80 and 319, as this approximately corresponds to the period without snow cover. Applying a cloud cover threshold of less than 80 % resulted in 821 images across the three footprints in our study area (Figure II-1). The images were not equally distributed over the years, but featured a period of particularly low data availability during the late-1980s and mid-1990s. While wheat can be separated from grassland in intensively managed systems, cropping in Kazakhstan often does not reach highest productivity (e.g. due to low fertilizer inputs), leading to confusion with grasslands. To allow differentiating croplands from grasslands, we therefore used multi-season imagery. For some years (e.g., 1984, 1997, 2003) no imagery was available from spring (plowing season, DOY 132 to 167) or fall (harvesting season, DOY 231 to 294), although these seasons are critical for separating croplands from grasslands (Prishchepov et al., 2012b; Baumann et al., 2015) as recently plowed or harvested fields allow most reliable distinction from the other land covers. To compensate, we used a temporal moving window of three years to generate spectral variability metrics (Griffiths et al., 2013b) as a first step to overcome data scarcity. These metrics statistically describe the time series of spectral values, are relatively robust to noise and seasonal fluctuations, and can serve as an input for classification algorithms (Zhu, 2017). Within each moving window, we derived the per-pixel minimum, median, maximum, mean, standard deviation, and percentiles (5, 25, 75, and 95) for the red, green, blue, NIR, SWIR1, and SWIR2 bands. In addition, we calculated the Normalized Difference Vegetation Index (NDVI), the Normalized Burn Ratio (NBR) and the Modified Soil-Adjusted Vegetation Index (MSAVI2) from which we derived the same metrics as for the six Landsat bands. In total, this yielded a set of 81 input features for each year.

2.3 Trajectory analyses to map the timing of abandonment and recultivation

Abandoned areas spectrally align along a gradient between cropped and uncropped areas. This is represented well in class probabilities of cropland vs. non-cropland classes (Yin et al., 2014, 2017). We thus derived cropland probabilities between 1985 and 2015 which then served as input for a trajectory-based approach to detect abandonment and recultivation events over time. This allowed omitting the high inter-annual spectral changes of cropland at the pixel level. Another advantage of using probabilities is their robustness against mixed pixels in the land cover class of interest (Colditz et al., 2011; Yin et al., 2014).

We used random forest classification (Breiman, 2001; Pedregosa et al., 2011) to map cropland probabilities for each year using the annual Landsat spectral variability metrics as predictor variables. We chose random forests because of the model's strength in dealing with classification problems that contain non-normal class distributions and heterogeneous input data (Abdel-Rahman et al., 2014)(Breiman, 2001). Class membership probability in random forests is the proportion of tree votes for that class in relation to the total number of trees. We trained the random forest model with reference data collected over stable croplands (i.e., areas that were permanently cropped between 1985 and 2015) and stable non-croplands (i.e., areas that were never cropped) based on visual interpretation of the Landsat time series (Cohen et al., 2010). We collected 900 sample pixels for each of the stable classes (i.e., cropland and non-cropland), as this enabled us to use a single training dataset for subsequently estimating cropland probabilities for each year. We identified agricultural fields considering their respective spectra, shape information and texture. The latter two were only used for visual interpretation. The non-cropland class included both managed and semi-natural grasslands, as well as water, urban land, forests, sand, wetlands, and salt marshes ("*solonchak*"). This resulted in annual maps of cropland probabilities for our study area.

We then used the temporal segmentation and change detection algorithm LandTrendr (Kennedy et al., 2010) on the annual time series of cropland probabilities to map the timing of cropland abandonment (Figure II-2). By fitting a series of linear segments using LandTrendr, we further reduced remaining inter-annual noise while capturing abrupt change events and gradual change. LandTrendr was originally designed to analyze forest disturbances, but recent applications suggest its suitability in identifying cropland dynamics as well (Yin et al., 2017, 2014).

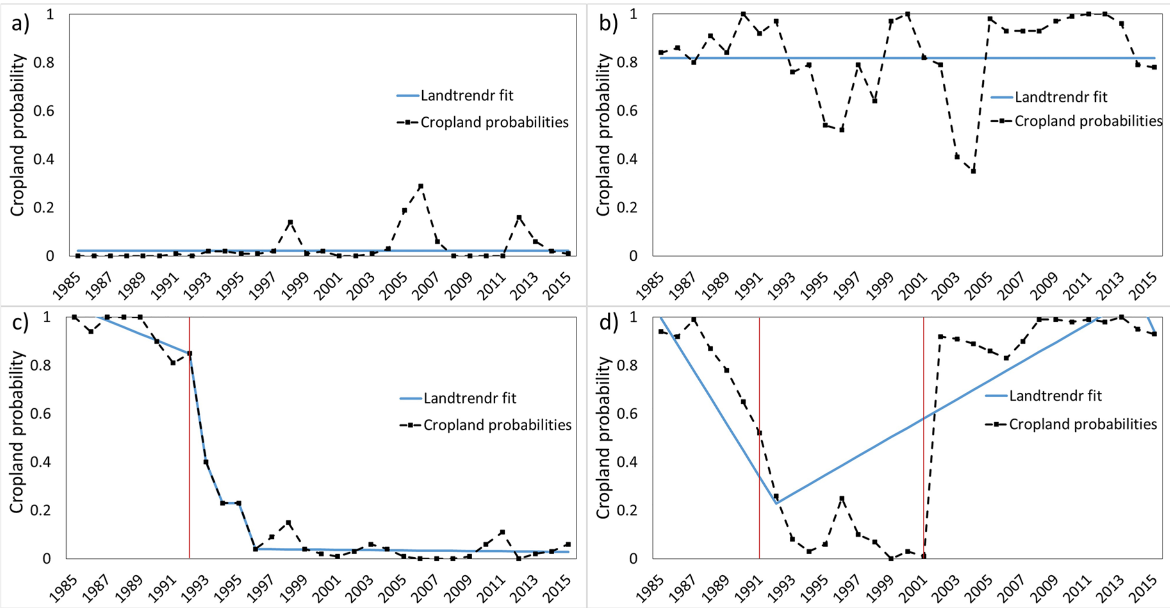

Figure II-2: Cropland probability time series and LandTrendr fit. Black: cropland probability for the respective year. Blue: LandTrend segments. Examples for (a) stable non-cropland, (b) stable cropland with crop rotation and intermittent fallow years, (c) abandonment, and (d) abandonment and recultivation. Red vertical line: the breakpoints detected by our algorithm.

To initiate LandTrendr, four main parameters need to be set. First, a *maximum segments* parameter limits the number of trend segments allowed during the fitting process. Second, *the de-spiking* parameter limits the influence of single outliers with higher values resulting in less smoothing, but also less consequent spike elimination. Third, a *recovery threshold* determines the maximum length of segments representing a positive trend. All three parameters are useful for separating short-term cropland-grassland cycles from long-term abandonment signals, as one or two fallow years may be falsely identified as abandonment. Lastly, LandTrendr requires setting the so-called *p-of-F value* that determines the goodness-of-fit. We tested different values of these parameters and selected the best combination by visually evaluating both the pixel-wise trajectory fit (using ca. 50 samples) and the parcel-wise homogeneity. We considered a parcel homogeneous when pixels of the same value (e.g., the same year of abandonment) were grouped in a shape typical for agricultural fields. We then fit two LandTrendr models: one to detect cropland abandonment, and a second one for detecting recultivation. We were then able to set the *maximum number of segments*, *de-spiking* and *recovery* parameters individually for both land-use change processes, which allowed handling the different spectral-temporal nature of abandonment as opposed to recultivation. We define an area as being abandoned when three consecutive years with cultivation were followed by three consecutive years without cultivation. We deliberately omitted areas that are not in line with our definition of abandonment (i.e., we accounted for up to two fallow years, or drought years).

We applied a rule-based filter to the LandTrendr-segmented probability time series to determine whether and when cropland was abandoned or whether it was fallow in a given year. We did this by analyzing the time series based on a temporal moving window of six years (Figure II-3). We considered a cropland pixel as representing abandonment in a particular year if the average cropland probability for three years was above a pre-defined threshold, followed by three years in which the average cropland probability was below the threshold. The exact year of abandonment was defined as the first year in which the cropland probability fell under the threshold. To empirically define a probability threshold, we tested values of 0.45, 0.5, 0.55, and 0.6, produced an abandonment map based on each of the thresholds, and visually selected the most appropriate one i.e., the threshold that led to homogeneous parcels and plausible spatial patterns according to expert knowledge of the area.

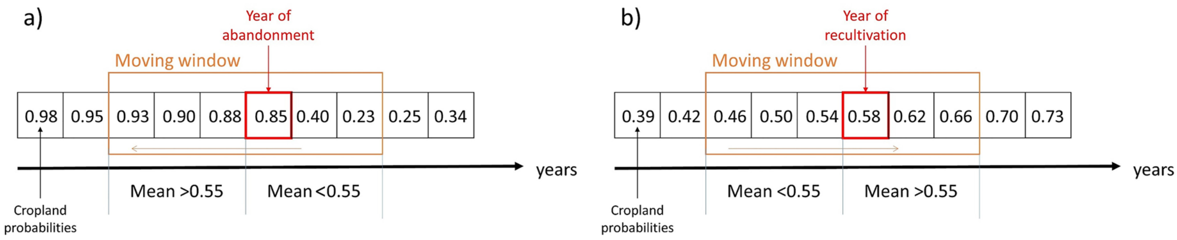

Figure II-3: Ruleset for detecting timing of (a) abandonment and (b) recultivation within a moving temporal window of six years. Cropland probabilities in the figure represent fitted LandTrendr outputs of typical abandonment and recultivation cases.

We also identified recultivated croplands that were previously abandoned for at least three consecutive years. Similar to the detection of abandonment, we categorized a pixel as representing recultivation if the mean cropland probability value for the first three years of recultivation was below a pre-defined threshold and the mean cropland probability before recultivation was above the threshold. We then defined the year of recultivation as the first year when the cropland probability was above the threshold (Figure II-3). Analogous to the abandonment detection, we tested a range of thresholds.

2.4 Map validation

To validate the abandonment and recultivation maps, we followed the good practices for accuracy assessments (Olofsson et al., 2014) based on a stratified-random sample of validation points derived from visually interpreting the Landsat time series and high-resolution imagery in Google Earth, if available (Cohen et al., 2010). We did two types of accuracy assessments for which we collected independent validation data. First, we validated the classification of stable croplands, stable non-croplands, abandoned croplands and recultivated croplands. Then, we assessed the accuracy of the annual abandonment and the annual recultivation maps. We randomly selected 50 pixels from each stable class and 30 pixels per year from the abandoned cropland classes (30 x 25 years = 750 samples). To adequately assess recultivation, we selected 20 pixels per class (i.e., per year) during the last 22 years, as there were not enough points representing recultivation from the first dataset. Thus, we selected 1,290 independent reference samples in total.

Considering the gradual spectral change on abandoned land and, consequently, the complicated nature of visually identifying abandoned croplands, we applied a fuzzy validation approach allowing a confidence interval of +/- 1 year. We then generated a confusion matrix, and estimated the overall accuracy and user's (UA) and producer's accuracies (PA) including the corresponding standard errors by adjusting for the unequal probability sampling (Olofsson et al., 2014). We also calculated area estimates and associated confidence intervals (Olofsson et al., 2014).

As a final confidence check, we compared our results to field-based estimates of the timing of cropland abandonment. We used 115 quadrats of 10x10 m² from a vegetation survey carried out in Kostanay province in 2015 and 2016 and followed the methods described in Brinkert et al. (2016). All plots were categorized into seven land-use classes, namely (1) croplands under cultivation, (2) recently abandoned croplands (after ca. 2011), (3) medium-long abandoned croplands (between ca. 2000 and ca. 2011), (4) longer-term abandoned croplands (before ca. 2000), (5) fodder grass fields (cut for hay, sown with crested wheatgrass *Agropyron cristatum*), (6) heavily grazed steppe, and (7) ungrazed ('pristine' steppe). The distinction between the different time periods of land abandonment was based on the dominance of plant species that are characteristic for certain age stages of abandoned fields in Kazakhstan (Marinych et al., 2002; Brinkert et al., 2016). Recently abandoned croplands are characterized by high cover of annual plants, medium-old ones by the dominance of certain *Artemisia* (wormwood and sagebrush) species, and the oldest ones by a higher cover of native steppe grasses of the genera *Stipa* and *Festuca*. For our study, we lumped classes 5–7 into one 'non-cropland' category. We categorized the map classes from the remote sensing analysis accordingly and compared the time since abandonment estimated in the field to our abandonment map. Finally, we summarized the results in a confusion matrix.

2.5 Assessing the influence of image availability

We extracted the number of available clear-sky observations for each pixel and year for the time periods used to compute the spectral variability metrics to study how image availability affected the accuracy. First, we analyzed the difference between the year of abandonment detected by our algorithm and the year according to the reference from the validation dataset. We then assessed how this difference related to the number of images available in the year of abandonment according to our map, and the year of abandonment according to the reference. Finally, we investigated the difference in the number of scenes in temporal windows around the actual abandonment year (reference data) and the year of detection based on the Landsat time series.

2.6 Assessing the impact of the timing of abandonment

Using our time series of cropland abandonment, we carried out two comparisons to demonstrate the value of knowing the exact timing of abandonment. First, we calculated the overall area of abandonment and recultivation for each year, as well as corresponding change rates between the years. We also calculated the number of years since abandonment and marked a year of abandonment for each pixel that we identified as 'recultivated' to understand if recultivation primarily occurred on recently abandoned croplands or on those abandoned earlier.

Second, we compared soil organic carbon (SOC) sequestration rates on abandoned croplands between our temporal exact information of abandonment, and for two scenarios assuming (a) that all abandonment occurred in 1990, and (b) assuming that all abandonment occurred in 2010. This represented scenarios one could assume for situations where cropland abandonment was mapped for broad time-intervals only, corresponding to prior existing research for the region. To estimate the difference in post-abandonment SOC sequestration, we combined SOC sequestration rates from an extensive field study for the region, based on 470 field plots (SOC stock in 0-5 cm ~ 0.066 kg/m2/year, Wertebach et al., 2017) with the area estimates from our classification. We calculated annual SOC sequestration as well as SOC sequestration for the entire period 1990-2010, considering the confidence intervals in area estimations from our classification to calculate upper and lower confidence levels around our SOC sequestration estimates.

3 Results

The overall accuracy of the aggregated map (i.e., one abandonment and recultivation class) was 88.8 %. UA was highest for the abandonment class (93.3 %) and lowest for the recultivation class (73.0 %). PA was highest for the recultivation class (95.1 %) and lowest for the abandonment class (65.2 %, Table II-1). For the annual abandonment map and annual recultivation map (Figure II-4), classification accuracies for the individual years were lower and varied strongly between individual years. The overall accuracy of the maps with yearly abandonment classes and yearly recultivation classes was 80.0 % and 88.0 %, respectively. For the year 2013, we achieved the highest UA (97.4 %). On the contrary, for 2004 our UA was only 14.9 %. The highest PA were achieved in 2006 (100.0 %) and lowest PA were achieved in 2004 (25.3 %; Table II-2). Similarly, UAs for the recultivation map varied between 100.0 % (2008 and 2010) and 14.5 % (1995), as did PAs (100.0 % for 1992-1994, 1996-1999, 2012; 54.8 % for 2003).

Table II-1: Accuracy assessment of the aggregated map of abandonment and recultivation (disregarding the year of abandonment/recultivation).

Class	*User's Accuracy (standard error)*	*Producer's Accuracy (standard error)*	*Area Proportion Estimate (standard error)*
Stable Cropland	0.84 (0.02)	0.93 (0.01)	0.321 (0.014)
Stable Non-Cropland	0.93 (0.01)	0.94 (0.01)	0.455 (0.012)
Abandonment	0.93 (0.02)	0.65 (0.02)	0.180 (0.014)
Recultivation after abandonment	0.73 (0.05)	0.95 (0.03)	0.044 (0.006)

When assessing the reliability of our maps using a fuzzy accuracy assessment classification, accuracies increased moderately. For the abandonment map, the overall classification accuracy increased by 3.8 % and for the recultivation map by 1.6 %. We found stronger increases in classification accuracies for individual years. On average, per-year UAs and PAs increased by 20.3 % and 24.2 %, respectively, in our yearly abandonment maps and by 24.0 % and 34.0 % for UAs and PAs, respectively, in our yearly recultivation maps.

Comparing our mapping results to the field-based timing of abandonment generally showed high agreement. Overall, 76 % of the classes in our map showed an agreement with the categories from the field inventories based on vegetation composition (Table II-3). In 57.4 % of all cases the mapped year of abandonment differed by +/- 1 year compared to the validation data and 70.8 % matched within +/- 3 years (Figure II-6). Our algorithm tended to identify the year of cropland abandonment later than in the validation dataset (Figure II-6 and Figure II-7). This trend correlated with the number of images available for the yearly cropland classification (Figure II-7 and Figure II-8). For example, the difference between the number of scenes in a temporal window of 6 years rarely exceed 50 when the difference in abandonment year detected visually vs. by our algorithm was < 5 years, but much higher (up to 200 images) if the difference in abandonment year was high.

According to our area estimation, ~4.7 million ha of the study area were cultivated as cropland in 1985, equaling 59.8 % of the region. By 2013, 1.8 million (~40.5 %) ± 54,000 ha of the previously cultivated land was abandoned. More cropland was abandoned between 1988 and 2000 compared to 2000-2013. The maximum annual abandonment of ~250,000 ± 73,000 ha we found for the year 1995, equaling 13.0 % of all cropland abandonment for the entire period (Figure II-5). Contrarily, we found the smallest area of abandonment in 2012 (~7,000 ± 10,000 ha, 0.3 %).

Table II-2: Fuzzy accuracy assessment per year.

Class	**Abandonment**		**Recultivation**	
	User's Accuracy (standard error)	*Producer's Accuracy (standard error)*	*User's Accuracy (standard error)*	*Producer's Accuracy (standard error)*
1988	0.46 (0.13)	0.38 (0.10)	-	-
1989	0.71 (0.21)	0.38 (0.12)	-	-
1990	0.86 (0.16)	0.48 (0.12)	-	-
1991	0.76 (0.19)	0.48 (0.13)	0.78 (0.17)	0.80 (0.15)
1992	0.71 (0.21)	0.64 (0.18)	0.63 (0.41)	1.00 (0.00)
1993	0.74 (0.15)	0.47 (0.10)	0.39 (0.48)	1.00 (0.00)
1994	0.74 (0.13)	0.48 (0.09)	0.76 (0.36)	1.00 (0.00)
1995	0.73 (0.13)	0.25 (0.05)	0.14 (0.37)	0.76 (0.99)
1996	0.79 (0.12)	0.36 (0.07)	0.32 (0.49)	1.00 (0.00)
1997	0.52 (0.17)	0.41 (0.12)	0.51 (0.46)	1.00 (0.00)
1998	0.79 (0.13)	0.31 (0.06)	0.34 (0.42)	1.00 (0.00)
1999	0.38 (0.12)	0.33 (0.09)	0.19 (0.16)	1.00 (0.00)
2000	0.36 (0.18)	0.49 (0.20)	0.25 (0.20)	0.90 (0.25)
2001	0.19 (0.10)	0.59 (0.20)	0.52 (0.26)	0.64 (0.23)
2002	0.20 (0.10)	0.81 (0.19)	0.87 (0.19)	0.68 (0.19)
2003	0.23 (0.11)	0.72 (0.20)	0.63 (0.29)	0.55 (0.23)
2004	0.15 (0.15)	0.25 (0.22)	0.69 (0.32)	0.67 (0.28)
2005	0.19 (0.16)	0.50 (0.31)	0.70 (0.21)	0.59 (0.17)
2006	0.23 (0.21)	1.00 (0.00)	0.59 (0.22)	0.83 (0.18)
2007	0.38 (0.22)	0.81 (0.25)	0.59 (0.20)	0.82 (0.17)
2008	0.21 (0.22)	0.05 (0.05)	1.00 (0.00)	0.83 (0.15)
2009	0.34 (0.31)	0.73 (0.40)	0.86 (0.22)	0.60 (0.21)
2010	0.29 (0.36)	0.40 (0.41)	1.00 (0.00)	0.84 (0.18)
2011	0.36 (0.38)	0.66 (0.47)	0.79 (0.21)	0.79 (0.19)
2012	0.60 (0.46)	0.83 (0.39)	0.84 (0.19)	1.00 (0.00)
2013	0.97 (0.10)	0.76 (0.20)	0.30 (0.15)	0.77 (0.21)
Cropland	0.88 (0.59)	0.93 (0.41)	0.84 (0.02)	0.93 (0.01)
Non-cropland	0.93 (0.35)	0.94 (0.31)	0.94 (0.01)	0.95 (0.01)
Abandonment	-	-	0.93 (0.02)	0.65 (0.02)

Figure II-4: Maps of abandonment timing in northern Kazakhstan from 1988 to 2013 (a), recultivation timing in northern Kazakhstan from 1991 to 2013 (b), and years between the abandonment and recultivation (c). N.R. means not recultivated as for 2013.

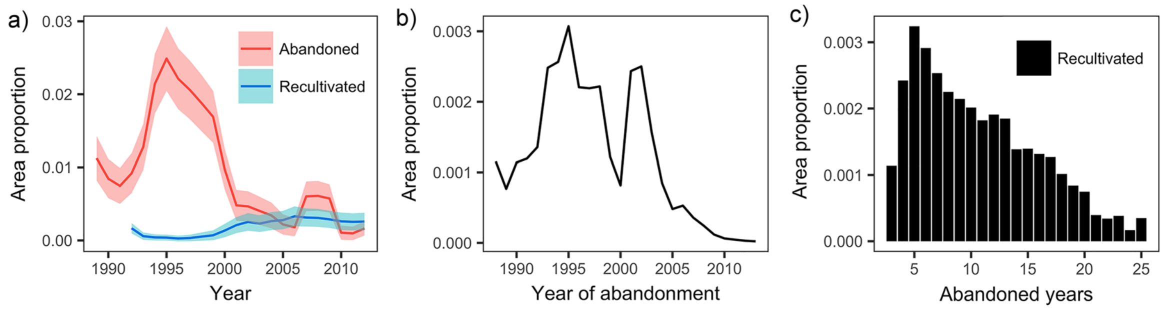

Figure II-5: Analysis of dynamics of cropland abandonment and recultivation in 1988-2015. (a): red - area proportion of abandoned land, blue - recultivated land, both with respective standard error, (b): year of abandonment event on recultivated parcels. (c) duration of fallow period before recultivation.

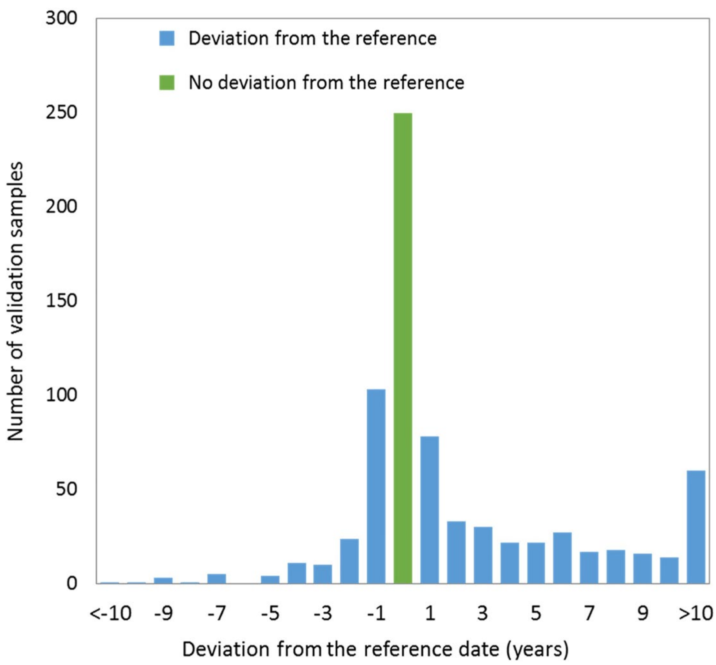

Figure II-6: Deviation of abandonment dates relative to the reference dataset.

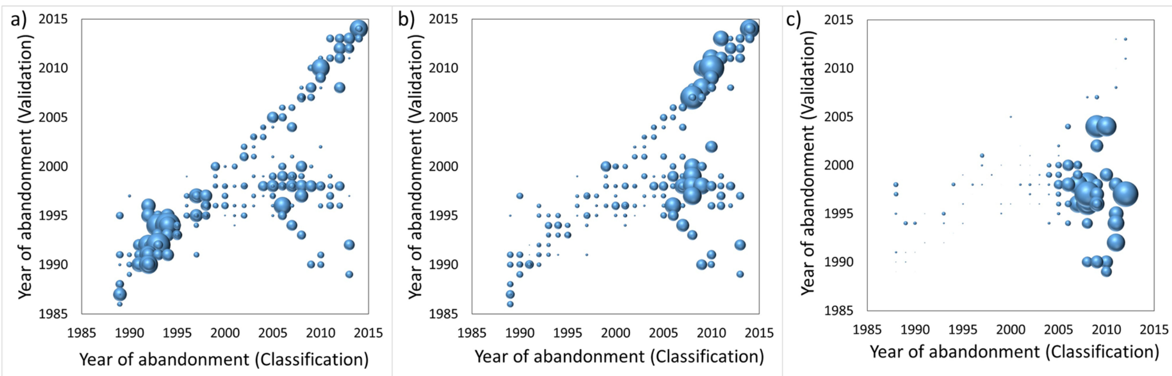

Figure II-7: Scatter plots of the abandonment date detected by our algorithm versus dates detected by visual interpretation. The size of the points represent: a) the number of scenes used in spectral variability metrics in a year of abandonment according to visual interpretation; b) the number of scenes used in spectral variability metrics in a year of abandonment according to automatic detection; c) a difference between the number of scenes used in spectral variability metrics in a year of abandonment according to visual interpretation and the number of scenes used in spectral variability metrics of a year of abandonment according to automatic detection.

Table II-3: Confusion matrix according to vegetation plots based on field observations.

	Reference					
Classification	*Non-cropland*	*Abandoned after 2010*	*Abandoned between 2000 and 2009*	*Abandoned before 2000*	*Cropland*	*Sum*
Non-cropland	59		2	6	1	68
Abandoned after 2010		2				2
Abandoned between 2000 and 2010			4			4
Abandoned before 2000	6	1	1	2	2	12
Cropland	3	3	1		22	29
Sum	68	6	8	8	25	115

A substantial proportion of the abandoned cropland had been recultivated by the end of our study period in 2013, with ~350,000 ± 54,000 ha recultivated by that time (20.0 %). Recultivation peaked in 2005, when ~32,000 ± 20,000 ha were recultivated (8.0 % of all recultivation), while lowest recultivation rates occurred in 1995 (2.2 % of all recultivation). Fields were more likely to be recultivated when abandonment had occurred less than 5 years ago (9.6 %). Moreover, once an area was abandoned for more than 13 years, it was much less likely to become recultivated (of all areas abandoned longer than 13 years, only 34.0 % were recultivated; Figure II-5).

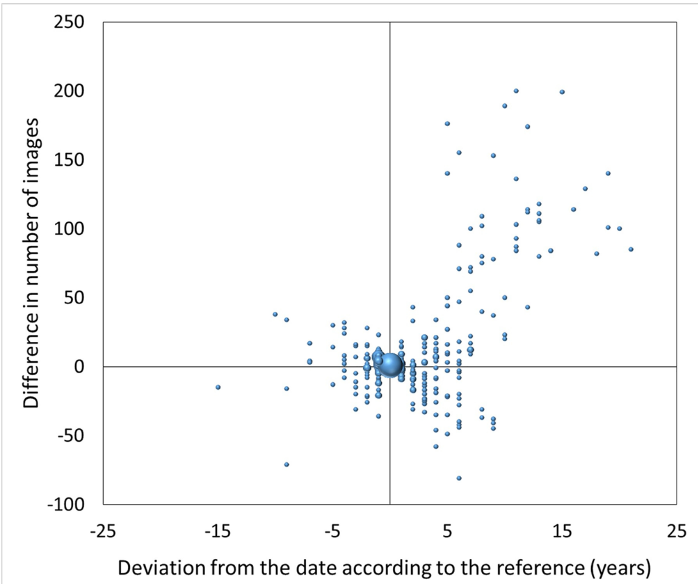

Figure II-8: Dependence of deviation of identified abandonment year on data availability. On horizontal axis is deviation of abandonment dates estimated by our algorithm from the dates according to the reference dataset. Vertical axis represents the difference between the number of scenes used for detecting abandonment using visual interpretation and the number of scenes used for detecting abandonment using automatic interpretation. The point size is proportional to the number of points with the same Cartesian coordinates of the plot (the size of the central bubble is reduced to 30 from 103 for visibility purposes).

Estimated SOC sequestration on abandoned cropland showed marked differences when based on our annual map (16.3 ± 3.5 Mt C) compared to scenarios that assumed all cropland abandonment had happened in 1990 (24.0 ± 5.8 Mt C) or in 2010 (3.3 ± 0.8 Mt C). Interestingly, the highest annual sequestration rate was fairly similar when comparing our map (1.07 Mt C for the year 2013) to the other two scenarios (1.09 Mt C). Likewise, the confidence intervals around the SOC sequestration estimates, both for the annual and overall calculation, became narrower when using our annual map (Figure II-9).

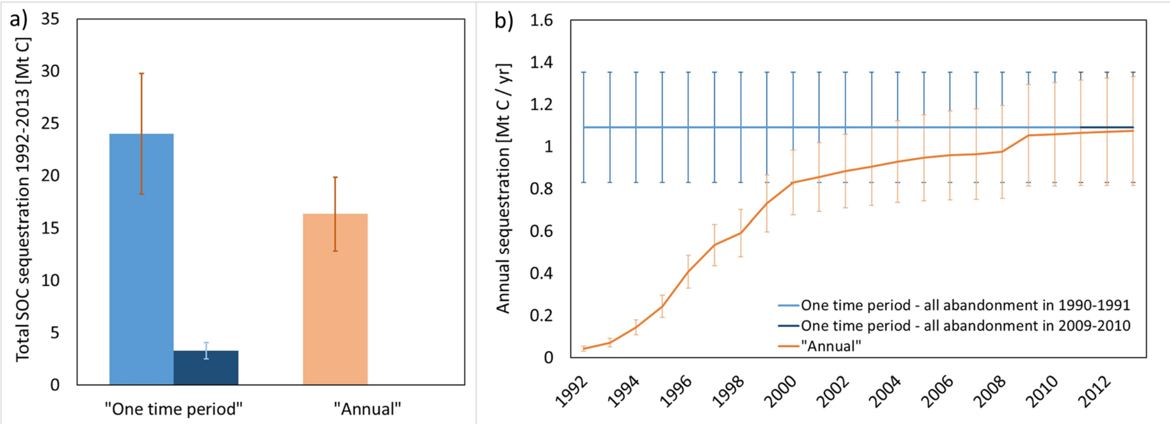

Figure II-9: Difference in estimates of a) total SOC sequestration and b) annual SOC sequestration rates when using annual estimates of abandonment area (in orange) versus assuming abandonment in 1990 (light blue) or in 2010 (dark blue). Confidence intervals are based on abandonment area estimates.

4 Discussion

Understanding spatial patterns and dynamics of agricultural abandonment is important to assess the potential of abandoned land for conservation, carbon sequestration, or agricultural production. However, existing cropland abandonment maps are either snapshots in time or lack the spatial detail needed to inform land managers at regional and national levels. To address this knowledge gap, we developed a trajectory-based method to map cropland abandonment and recultivation from annual Landsat time series. Our test area in northern Kazakhstan experienced widespread abandonment and recultivation as well as marked periods of image scarcity since the 1980s, all of which is representative for post-Soviet countries. Our study provides a number of key insights on how to utilize and optimize Landsat time series for monitoring agricultural dynamics such as land abandonment and recultivation at high temporal resolution.

First, our study demonstrates that it is possible to estimate the trends of cropland abandonment and recultivation timing in grassland regions. Using cropland probabilities classified from spectral metrics allowed us to account for inter-annual variability, and feeding these probabilities to the segmentation module of LandTrendr allowed mapping abandonment trajectories reliably in most years. Using all available Landsat data, we were able to detect the annual timing of cropland abandonment within +/- one year with an accuracy of 80 %, and the reliability of our maps was further confirmed by the comparison to in-situ vegetation plot data. Spectrally, cropland abandonment is a gradual, not a sudden change (Estel et al., 2015; Prishchepov et al., 2012b), which was likely better captured by our approach of using continuous cropland probabilities as input for our trajectory analyses (Yin et al., 2014) than when mapping abandonment based on image snapshots. Indeed, in the first years after abandonment former crop fields still had high cropland probabilities, and only after several years of abandonment these probabilities dropped.

A second major insight relates to the spatio-temporal patterns of abandonment that we found to have occurred in northern Kazakhstan after 1990. Our time series of abandonment revealed distinct episodes of cropland abandonment in our study area. The first of these episodes occurred right after the breakdown of the Soviet Union (1993-1999), when the vast majority of this abandonment occurred because of rural outmigration, loss of guaranteed market, and reduced funding of the agricultural sector as well as reduced profits in agriculture (Henebry, 2009; Ioffe and Nefedova, 2004). These areas that have been abandoned for a long time are likely those that are least profitable to cultivate, that is, where agroecological conditions are worst (Prishchepov et al., 2013), and socio-economic constraints strongest (Meyfroidt et al., 2016). With the breakdown of the Soviet Union and the associated declining subsidies, such areas became permanently unattractive to farmers (Prishchepov et al., 2013). Interestingly though, a second, significantly smaller wave of abandonment appeared to occur in 2007-2009, explained rather by poor infrastructure (Meyfroidt et al., 2016). Indeed, in marginal regions of our study area, cropland abandonment even continued after recultivation started elsewhere. Our approach based on annual time steps allowed the discovery of these complex land-use change patterns, because this second wave of abandonment was superposed by an increasing recultivation trend due to an increase of subsidies from the government (Meyfroidt et al., 2016). The recultivation wave started in 2001 and reached the rates of abandonment by 2003, dropped slightly afterwards, and stabilized by 2008.

We compared our abandonment map to the only other existing Landsat-based map we know of for Kazakhstan (Kraemer et al., 2015). Our map shows smaller rates of abandonment (26 % between 1990 and 2010), compared to 45 % in(Kraemer et al., 2015). We suggest our estimate is more reliable and this difference can mainly be explained by crop rotations. Studies based on two time periods (Kraemer et al., 2015; Baumann et al., 2011; Prishchepov et al., 2013) only overestimate abandonment area due to fallowing, which is widespread in the study region. An alternative explanation could be that our approach underestimated abandonment in the 1990s due to a tendency for time-delayed abandonment detection, but the substantially higher overall accuracy in our study (88 % compared to 78 % in (Kraemer et al., 2015)) suggests this plays a lesser role in explaining the different abandoned area estimates of the two studies.

A third major insight from our study was that about one fifth of all abandoned croplands had been recultivated by 2013. Most of these areas were located in more fertile and productive areas with Chernozem soils (based on a qualitative comparison to soil samples taken at the vegetation plots we used), again indicating that recultivation primarily occurred in areas where farming conditions are best. This is in line with existing research on the post-Soviet region (Prishchepov et al., 2012a; Meyfroidt et al., 2016; Kraemer et al., 2015; Griffiths et al., 2013a). This indicates a spatial reorganization of agricultural production in northern Kazakhstan towards the most profitable areas.

A fourth major insight was that image availability substantially influenced the ability to accurately determine the timing of abandonment and recultivation. For some years, accuracy was much lower, especially during the early 2000s. A similar effect was found in earlier pan-European work (Estel et al., 2015), and we suggest at least two factors may explain these lower accuracies. First, despite ongoing Landsat archive consolidation (Wulder et al., 2016), wide areas of Central Asia continue to be relatively data scarce for the 1990s. As a consequence, our spectral metrics during these years may not have been as robust as compared to the 1980s, or 2000s, when more imagery are available (Wulder et al., 2008). For example, fewer images can be expected to lead to higher variability in spectral metrics of abandoned areas (e.g., due to a higher influence of outliers or phenology), and this might obscure abandonment signals, resulting in a delayed detection of abandonment (Figure II-7). Moreover, it is difficult to detect croplands when the spectral breakpoints related to plowing and harvesting are missing in the time series, or no-till technology is applied, as it is increasingly the case in recent years in our study region. No-till farming leads to less abrupt changes in the abandonment (or recultivation) signal and generally decreases the signal-to-noise ratio of the time series (i.e. time series variability compared to the signal-change related to non-cropping). Second, even after cultivation ceased, the spectral characteristics of abandoned fields can remain similar to managed cropland for a while (Estel et al., 2015; Prishchepov et al., 2012b), such as when crops from previous years dominate successive vegetation (Carson and Barrett, 1988), or crop residue retention (i.e., when farmers keep stubble longer than usual in order to detain snow on the field) is practiced (Kienzler et al., 2012). Field observations and conversations with local farmers suggest both can occur in our study area for up to 3 years, explaining smaller timing errors. Another reason for lower user accuracies in years 1999-2013 is the small area proportion of the abandonment class during these years. Our maps thus might underestimate land-use change for these years. However, it is important to note that our area estimates are not retrieved from the maps, but instead calculated using a post-stratified estimator and the probability sample of visually interpreted plots, thus accounting for classification uncertainty (see(Olofsson et al., 2014). Despite related uncertainties, we emphasize that our approach resulted in a map that allowed identifying the timing of abandonment within +/- one year in the majority of cases, highlighting the value of long time series of Landsat data.

A final key insight from our study was the value of knowing the timing of abandonment for a better understanding of agricultural land-use change and its environmental impacts. Our results showed that abandoned croplands were less likely to become recultivated the longer they stayed abandoned, especially if they were abandoned for five or more years. As explained above, the least profitable areas with poorer soils were abandoned first. Similarly, accurate information on the timing of abandonment can help to better estimate the environmental outcomes of abandonment, as in our assessment of SOC sequestration on abandoned croplands. Without precise abandonment maps, estimations of SOC sequestration could be either under- or overestimated (the first by 80 %, and the latter by up to 47 %), and the uncertainty around these estimates is much lower than without annual time series. Much research effort has gone into quantifying the terrestrial carbon sink that has emerged due to cropland abandonment in the post-Soviet sphere (Kurganova et al., 2014; Schierhorn et al., 2013; Vuichard et al., 2008), and our study highlights the need for incorporating time series of abandoned and managed cropland for making these estimates more accurate. Similarly, the biodiversity value of abandoned cropland largely depends on the time since abandonment, with older sites being closer to natural steppes in terms of species composition and structural and functional characteristics (Brinkert et al., 2016; Kamp et al., 2011; Kämpf et al., 2016). Knowing the timing of abandonment is thus important from a conservation perspective as well, as it would allow researchers to target those areas with the highest carbon accumulation and the lowest chance of being recultivated (Gerla et al., 2012), thus minimizing conflicts due to competing land-use interests.

Our analyses yielded robust and plausible abandonment maps, but a few uncertainties remain. First, LandTrendr may confuse shorter fallow periods with abandonment, but visual comparison of more restrictive threshold suggests this effect is minor in our case. Furthermore, we consider only one abandonment event per pixel, while in theory more complex land-use change patterns are possible. Third, our method reduces the time series length. Although we used imagery from 1984 to 2016 (32 years), our temporal moving window approach reduced this to 30 years, and our trajectory ruleset allowed for abandonment mapping only between 1988 to 2013 (25 years) and recultivation mapping from 1991 to 2013 (22 years). Finally, following our definition of recultivation we only mapped cropland expansion on previously abandoned areas. However, to our knowledge there was no significant cropland expansion in previously unplowed areas. Despite these limitations, we suggest that our method has great potential to be used in similar areas, provided adequate training data for croplands and non-croplands exists. Our method can be flexibly scaled and thus should be applicable to larger areas as well.

The opening of the Landsat archive provides unprecedented opportunities to reconstruct land-use and land-cover change histories back to the 1980s based on dense image time series of high-resolution imagery since the 1980s. So far, these opportunities have mainly been leveraged for mapping dynamics in forest cover, but our study highlights the value of the Landsat archives for an improved agricultural monitoring as well. Our approach to combine class probability time series with trajectory approaches overcame two challenges common to agricultural monitoring, with the high spectral within-class variability on the one hand and data sparseness common for many world regions on the other. Finally, our study highlights the possibility of Landsat to provide more accurate land-use/cover change maps in steppe regions, which have been understudied, and thus providing baseline information for conservation planning and land-use planning.

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Chapter III:
Post-Soviet land-use change affected fire regimes on the Eurasian steppes

Ecosystems (in review).

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Abstract

Fire is an important disturbance in grassland ecosystems. Anthropogenic factors, especially land use, have drastically altered fire regimes in many regions, but how changing land-use intensity affects fire patterns remains weakly understood. Here, we reconstruct changes in fire regimes between 1989 and 2016 for the understudied Eurasian steppes, where major land-use changes happened after the dissolution of the Soviet Union in 1991. We mapped burned areas in a 540,000 km^2 study region in northern Kazakhstan for three-year periods centered on 1990, 2000 and 2015, based on all available Landsat imagery. We then used these maps to assess changes in the extent, number and size of fires over time, and to explore links between changes in fire regimes and agriculture. We found a sevenfold increase in total burned area and an eightfold increase in fire numbers between 1990 and 2000. After 2000, burned area and fire numbers declined slightly, while fire size remained stable. Most of the observed increase in fires in the 1990s occurred on cropland, most likely due to agricultural burning. The abandonment of cropland and pastures was also associated with intensified fire regimes, likely due to increased aboveground biomass and thus higher fuel loads. Overall, our results suggest that intensifying fire regimes on the Eurasian steppe are clearly linked to post-Soviet changes in agriculture. Given that fires on Eurasia's steppes have wide-ranging consequences, affecting regions as far away as the Arctic, better regulation of agricultural practices, better fire monitoring, and more pro-active fire management are needed.

1 Introduction

Grasslands are among the world's most extensive biomes, are biologically diverse, and play an important role as carbon sinks (Anderson, 1991; Scurlock and Hall, 1998b). In the natural grasslands of the temperate zone (steppes in Eurasia and prairie in North America), fire is a key ecosystem process. For example, steppe fires limit shrub and tree encroachment (D'Odorico et al., 2012; Van Auken, 2000). Many grasses are fire-dependent, and fires therefore shape steppe plant community composition (Collins and Calabrese, 2012; Morgan, 1999). At the same time, steppe fires contribute to carbon and nitrogen loss (Chen et al., 2017; Pellegrini et al., 2017), air pollution, global warming (Stohl et al., 2007), and can threaten human infrastructure and lives. It is therefore important to understand where steppe fires occur, and how and why fire regimes change.

In the Anthropocene, most fires are caused by people (Chuvieco et al., 2003; Smelyanskiy et al., 2015). The most common factors that affect fire regimes are changes in climate and agricultural practices (Alvarado et al., 2017; Chuvieco et al., 2008; Vannière et al., 2008). Cropland management is a key land-use activity in steppe areas and a major source of ignitions, e.g. through sparks from agricultural machinery (Chuvieco et al., 2003; Smelyanskiy et al., 2015). More importantly, fire is an agricultural management tool, as farmers burn fields to remove straw residuals after harvest or before sowing to control disease and to facilitate plowing (McCarty et al., 2017). This causes major air pollution (Stohl et al., 2007) and has adverse effects on carbon sequestration and soil fertility. Agricultural burning to clean stubble fields is therefore prohibited in many regions, although farmers often ignore these bans (McCarty et al., 2017). Furthermore, cropland abandonment can lead to fuel accumulation, which can increase both fire frequency and fire intensity (Fuhlendorf et al., 2009; Moreira et al., 2011). Overall, the extent and frequency of fires related to changes in cropland management remain often unclear, as are effects on adjacent steppes.

Livestock grazing is another major agricultural activity in steppes with considerable implications for fire regimes. On the one hand, grazing may reduce fire rates and severity through the removal of fuel (Van Auken, 2000). On the other hand, fire is an important management tool in livestock husbandry, for example to clear woody vegetation or to increase the biomass and nutritional value of forage (Andreae, 1991). Where grazing ceases, both an increase (Dubinin et al., 2011) or decrease (Moreno et al., 2014) in fire frequency and extent has been observed (Moreira et al., 2011).

Steppes have been hotspots of land-use change across the globe, and given the clear links between agriculture and fire, these land-use changes likely altered fire regimes (Foley, 2005; Lambin and Geist, 2006; White et al., 2000). However, most existing work on fire and land use in steppes has focused on US prairies, while other steppe regions are understudied. One of these regions is the former Soviet Union, where land use has recently been particularly dynamic. Massive cropland expansion happened during Khrushchev's Virgin Lands campaign in 1954-1963, when ca. 45 Mha steppe were converted in just nine years (McCauley, 1976a). Following the collapse of the Soviet Union, 58 Mha of agricultural land were abandoned (Lesiv et al., 2018) and livestock numbers plummeted (Baydildina et al., 2000; Prishchepov et al., 2012a; Robinson and Milner-Gulland, 2003). More recently, some abandoned croplands were brought back into production, and livestock numbers partially recovered (Meyfroidt et al., 2016; Schierhorn et al., 2014). The Eurasian steppes, and especially the steppes in Kazakhstan, are a global fire hotspot (Archibald et al., 2013; Giglio et al., 2013). Between 2001 and 2009, nearly 90 % of all fires in the drylands of Central Asia occurred in northern Kazakhstan, affecting about 4 Mha of cropland-dominated and 10 Mha of grassland-dominated areas (Loboda et al., 2012). Increasing fire frequency has been suggested to affect the taxonomic and functional composition of steppe vegetation (Brinkert et al., 2016) and to increase carbon losses (Chen et al., 2017). Black carbon (soot and ash) drifts to and is deposited in the Eurasian Arctic (Stohl et al., 2007), and even haze over Alaska has been associated with Eurasian steppe fires (Warneke et al., 2009). Post-Soviet changes in agriculture (e.g., agricultural abandonment, changes in grazing pressure, agricultural burning) likely impact fire regimes in major ways (Dubinin et al., 2011). Yet, few studies have assessed links between agricultural land-use change and fire across larger areas in Eurasia's steppes.

Mapping fires back to the late Soviet era is therefore a first and necessary step for understanding changes in fire regimes. Yet, mapping grassland fires in Eurasia is challenging as steppe fires ignite, spread and die quickly. Ash is typically blown away by the strong steppe winds and in some areas fire scars are only visible for a few weeks as post-fire vegetation recovers rapidly (Arkhipkin et al., 2010). Furthermore, burned-area mapping is challenging due to the dark soils such as Vertisols, Kastanozems or Chernozems that are spectrally similar to burns (Hall et al., 2016; Zhu et al., 2017). Only a few studies have attempted to map fires in the region: Dubinin et al. (2010) mapped burned areas in the steppes of Russia using very coarse-resolution (8 km) Advanced Very High Resolution Radiometer (AVHRR) composited imagery, and Loboda et al. (2012) mapped fires across the drylands of Central Asia using Moderate Resolution Spectral Radiometer (MODIS) imagery (500 m). Unfortunately, these coarse-resolution sensors tend to omit many smaller fires (Hall et al., 2016; Hantson et al., 2013; McCarty et al., 2017) and MODIS extends only back to 2000, missing the Soviet fire regime baseline and the period of most drastic land-use change in the 1990s. Using the freely available Landsat image archive (30 m resolution, 1984-now) could potentially remedy these shortcomings (Wulder et al., 2008) and provide new opportunities for fire mapping (Hawbaker et al., 2017; Kovalskyy and Roy, 2013).

Fire maps allow to derive the extent, number, and spatial patterns of fire, which can be used to characterize fire regimes (Archibald et al., 2013) and changes in them (Andela et al., 2017). Fire regimes, in turn, can give insights into the drivers and consequences of fires, as well as fire management options (Archibald et al., 2013; Chuvieco et al., 2008; Moreira et al., 2011). For example, large fires are more difficult to extinguish than smaller burns, and may indicate different ignition sources (McCarty et al., 2017; Nagy et al., 2018). Integrating fine-resolution fire regime maps with land-use indicators may allow to attribute fire causes and thus to identify appropriate management responses. Yet, for the Eurasian steppes, this has not been carried out, mainly because spatial data on fire and land use, particularly on grazing, are sparse due to e.g., difficulties related to the Landsat archive consolidation (Kovalskyy and Roy, 2013; Loveland and Dwyer, 2012).

We focused on a 540,000 km² steppe area in northern Kazakhstan that is often highlighted as a global fire hotspot (Korontzi et al., 2006; Tansey, 2004). We were interested in understanding fire regime changes after the breakdown of the Soviet Union in relation to changes in agricultural management since new, fine-scale maps on cropland change have recently become available (Baumann et al., In review; Dara et al., 2018). Here, we combine these data with indicators of fire activity, based on Landsat imagery, and indicators of grazing pressure, based on screen-digitized locations of livestock stations, to unravel links between land use and fire for the time period 1989-2016. Our objectives were to:

1. Map burned areas in northern Kazakhstan's steppe region for the late Soviet period (1989-1991), the period of peak agricultural abandonment (1999-2001), and the period following the recent recultivation phase (2014-2016).

2. Assess changes in fire extent, numbers, and size to characterize fire regimes.
3. Assess links between changes in fire regimes and changes in cropping and grazing systems.

2 Methods

Our study area was located in the semi-arid temperate steppe zone of northern Kazakhstan (Figure III-1). Average annual temperature in the region is 2.8 °C, however, the climate is strongly continental (coefficient of intra-annual variation is 389 %), with hot arid summer temperatures exceeding 40 °C, whereas the cold and dry winters reach temperatures of -50 °C (Kamp et al., 2011). Precipitation varies from 200 mm in the south of our study area to 450 mm in its north, with a maximum in late spring and early summer. Rain-fed agriculture is restricted to areas with more than 250 mm annual precipitation. Dry periods favoring the outbreak of fires occur after snowmelt (i.e., April) or from July until the start of winter. The peak of the fire season is in the driest months of July and August (Loboda et al., 2012).

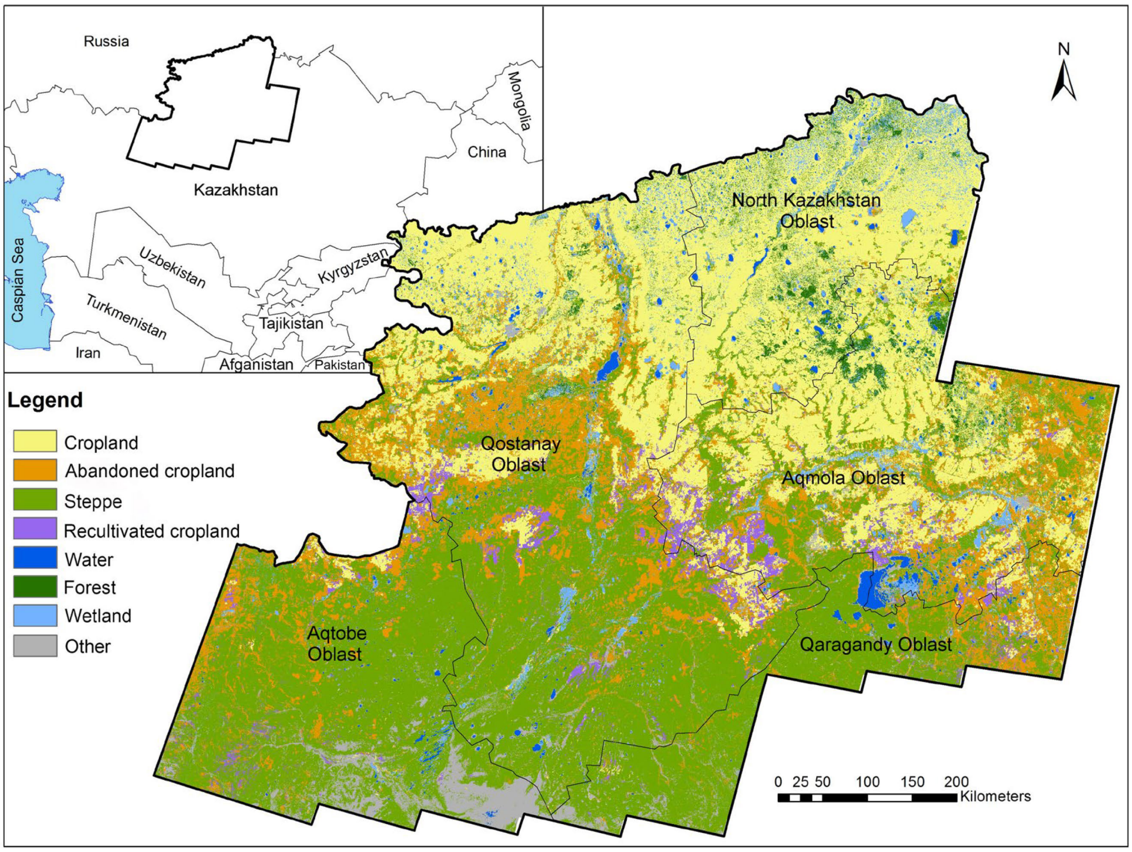

Figure III-1: Location of the study area in Central Asia (upper-left corner) and the main land covers/uses as of 2015. The northern part is mainly occupied by croplands, while both grazed and ungrazed steppe prevail in the south. Abandoned croplands are particularly widespread in the central part. There are some desert areas in the very south (included in “Other”).

Chernozems and Kastanozems are the most widespread soil types, with alkaline Solonetz soils found in depressions (Beznosov and Uspanov, 1960). Vegetation changes along the precipitation gradient from desert steppe in the south over dry steppe to forest steppe in the north. Natural steppe vegetation is dominated by feather grasses (*Stipa* spp.), fescue (*Festuca* spp.), wheatgrass (*Agropyron* spp.), as well as dwarf shrubs such as wormwood (*Artemisia* spp.) (Vorobyov and Belov, 1985). Sand dunes and saline lake depressions (solonchaks) appear in the south, while numerous wetlands and small forest patches with birches, aspens, and pines are found in the forest steppe (Gudochkin et al., 1968).

The northern part of our study area is predominantly used for spring wheat production. The cropping cycle typically starts in mid-May, when fields are tilled and directly sown. Tillage intensity declines towards the south with minimum till in the dry steppe. Harvest takes place from mid-August until mid-October. Farmers occasionally burn stubble in spring before sowing, or after harvest. According to a recent satellite-based assessment, 29 % of the croplands cultivated in 1990 had been abandoned by 2000 (see Figure SM III-3 for examples of agricultural abandonment), and an additional 7 % were abandoned by 2015 (Baumann et al., In review). However, 17 % of the croplands abandoned by 2000 were recultivated by 2015. The dominant land use in the southern part of the study area is livestock husbandry.

Cattle, sheep, and horses are the most numerous livestock in the area. In Soviet times, a large proportion of the livestock was owned by large, state-controlled agricultural enterprises. After the collapse of the Soviet Union, ownership changed, and across the Kazakh Steppe, about 80 % of the livestock are now owned privately and used for semi-subsistence. Until the late 1980s, livestock husbandry included elements of transhumance (Kerven et al., 2006), with livestock being moved from winter livestock stations (*zimovkas* in Russian or *kystau* in Kazakh) to summer stations (*letovkas* in Russian or *zhaylau* in Kazakh). After the breakdown of the Soviet Union, the system of livestock productions at large collapsed due to the loss of market access, diminishing subsidies, as well as the lack of qualified labor, machinery, and infrastructure. As a result, livestock numbers had declined by up to 80 % in sheep and 5 0% in cattle numbers until the late 1990s (Kamp et al., 2016), and have only partly recovered since. This led to the widespread abandonment of livestock stations and seasonal pastures (see Figure SM III-3 Figure SM III-7 for examples). The remaining herds were typically grazed on the same sites year-round

(Robinson and Milner-Gulland, 2003). This led to major changes in grazing pressure, with overgrazing around the few livestock stations and settlements that continued to have larger numbers of livestock, and drastically reduced grazing pressure across vast steppe areas that had been heavily grazed during Soviet times (Kamp et al., 2016; Kerven et al., 2006; Robinson et al., 2003).

2.1 Mapping burned areas from Landsat images

To map burned areas, we derived spectral-temporal metrics that statistically summarize the spectral information across all images available for a given time period (Frantz, 2017). This approach allows extracting all necessary information from sparse and temporally fragmented satellite images (Griffiths et al., 2013b). We derived 75 such spectral-temporal metrics for each pixel from all available Landsat imagery for the periods 1989-1991, 1999-2001 and 2014-2016 (Figure III-2; for more details on Landsat composite pre-processing, see Text SM III-1).

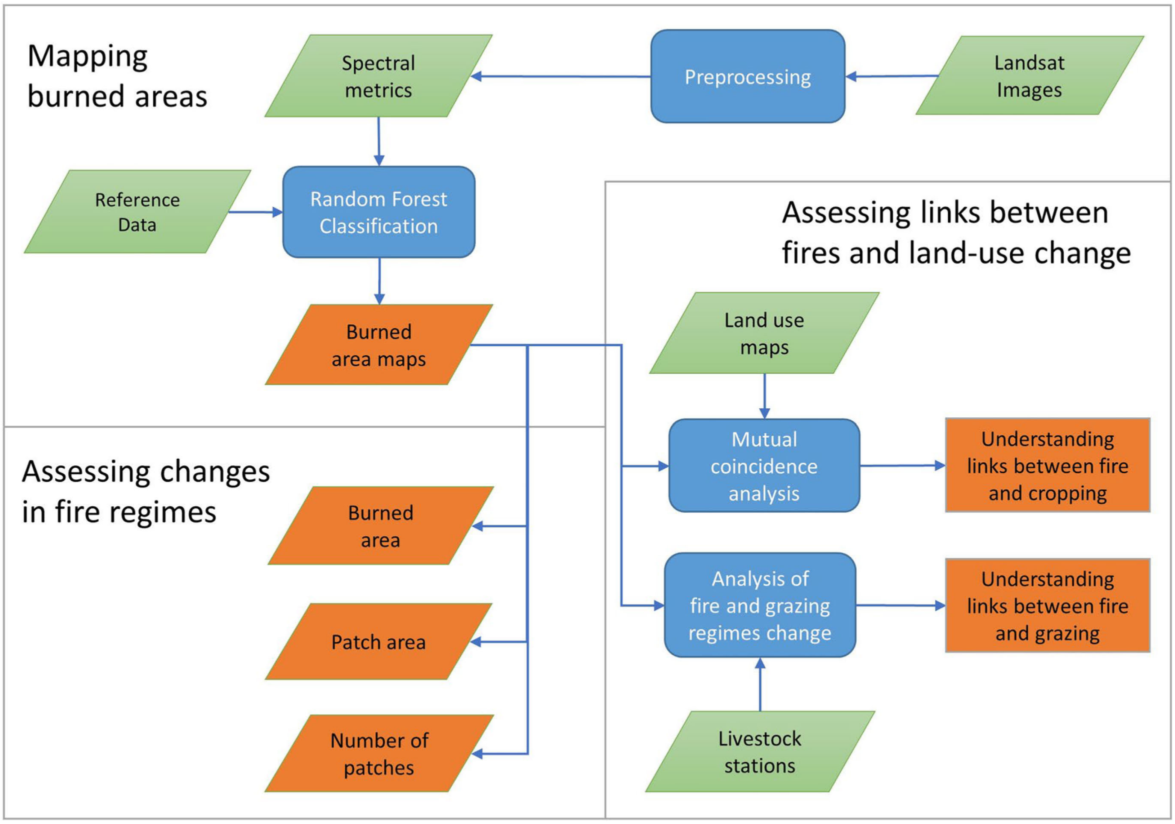

Figure III-2: Major steps of our analyses (blue) as well as their respective key inputs (green) and outputs (orange).

To derive burned area maps, we first collected reference data using visual interpretation of monthly Landsat Normalized Burn Ratio-Thermal (NBRT) composites (Holden et al.,

2005) time series and the MODIS burned area product (MCD64A1, available from 2001) in Google Earth Engine (Gorelick et al., 2017). We randomly allocated half of these reference points to a training, and the other half to a validation dataset. We used a random forest classifier (Breiman, 2001) to detect areas that burned at least once in a given three-year period. After training our random forest model, we classified the spectral metrics to produce a burned vs. unburned area map for each time period. We selected a minimum mapping unit of 100 pixels, after testing a variety of minimum mapping units, as a trade-off between the loss of small fire patches and increasing accuracy. We then validated our maps using the independent reference points following best-practice guidelines by Olofsson et al. (2014). For detailed information on the remote sensing analysis, please refer to Supporting Information (Text SM III-2).

2.2 Assessing changes in fire regimes

To characterize fire regimes, we selected three key fire regime attributes (Archibald et al., 2013): (1) fire extent, (2) number of fires, and (3) average size of individual fires. To assess fire extent, we calculated the proportion of burned area during each 3-year time step correcting for possible sampling bias (Olofsson et al., 2014) and compared the resulting figures. We used patch analysis as implemented in the *Fragstats* R package (McGarigal et al., 2002) to derive the number of burned-area patches per time period as a proxy for the number of fires. Lastly, we evaluated the distribution of fire patch areas per time period to derive proxies for average fire size and performed Wilcoxon rank sum test (Hollander and Wolfe, 1999) to check whether fire size significantly differed between the periods.

2.3 Assessing links between fires and land-use change

To investigate the links between agriculture and fire, we assessed fire regimes separately for different land-use/cover change classes (hereafter: land-use change classes) from Baumann et al. (In review). We performed a mutual coincidence analysis of burned areas and land-use change classes to compare, over time, the extent, number and size of fires between permanent cropland, permanent steppes, abandoned cropland, recultivated cropland.

We also investigated links between changes in grazing pressure and changes in fire dynamics. We anticipated that human population density and the associated density of herded (free-ranging) livestock were directly related to fire patterns. We therefore aimed to quantify changes in settlements and livestock stations from Soviet times to now. Livestock stations, across the former Soviet Union, are outposts on summer (‘Letovkas’) and winter pastures (‘Zimovkas’), where livestock is concentrated. Stations usually consist of up to three houses or tents (‘yurts’) for shepherds and a corral for livestock to shelter during the night. To estimate rates and patterns of change in settlement and livestock station density (hereafter: points of livestock concentration), we digitized livestock outposts and settlements for ca. 1984 (representing the still intact Soviet infrastructure) and ca. 2012 (representing the current situation). For the Soviet period, we manually digitized settlements, Letovkas, Zimovkas and all other livestock infrastructure across the study region (n = 6482) from official, georeferenced Soviet topographic paper maps scaled 1:200,000. For the 2012-period, we used very high-resolution satellite images from Google Earth and Bing to assess whether the points of livestock concentration were still intact and used. We visually inspected the settlements and livestock stations and estimated how much (in %) of the buildings were derelict compared to the end 1980s (0 %: no intact buildings left). Abandoned buildings are easily identified as they collapse quickly due to use of clay bricks for construction. Further evidence of complete abandonment of the livestock stations were the absence of dirt tracks and corrals. Active corrals are easily detected due to their quadratic shape and their dark color resulting from dung deposition.

We then used the points of livestock concentration to explore links between changes in livestock numbers and grazing pressure (as proxied via the changes in intactness of stations and settlements) and fire patterns. To do so, we established circular 500-m buffers around each livestock station and settlement, up to a distance of 10 km, as this is the maximum daily movement distance of herded livestock (e.g., Hankerson et al., 2019; Kamp et al., 2012; Kerven et al., 2006). For each buffer ring, we calculated the average share of burned area as well as the number of fires, separately for active (intactness >= 50 %) and abandoned (intactness < 50 %) livestock stations and settlements, and for each time step. Steppes outside the 10-km buffer around livestock stations and settlements were considered as ungrazed by livestock. We also calculated the same fire regime attributes for the entire 10-km radius around active and abandoned livestock stations, and around settlements.

3 Results

Our approach resulted in reliable burned area maps in northern Kazakhstan, with high overall accuracies of 99 %, 94 %, and 96 % for the 1990, 2000, and 2015 maps, respectively (Figure III-3; for more details on the accuracy assessment see Text SM III-2 and Table SM III-1). The burned area maps exhibited clear temporal and spatial patterns, suggesting a higher number of burned patches in the post-Soviet era (after 1991) compared to Soviet times. Burned area was concentrated in the southern, livestock-breeding-dominated part of the study area in 1990 and 2015, but we also observed a clear increase in fire activity in the cropland-dominated north of our study region.

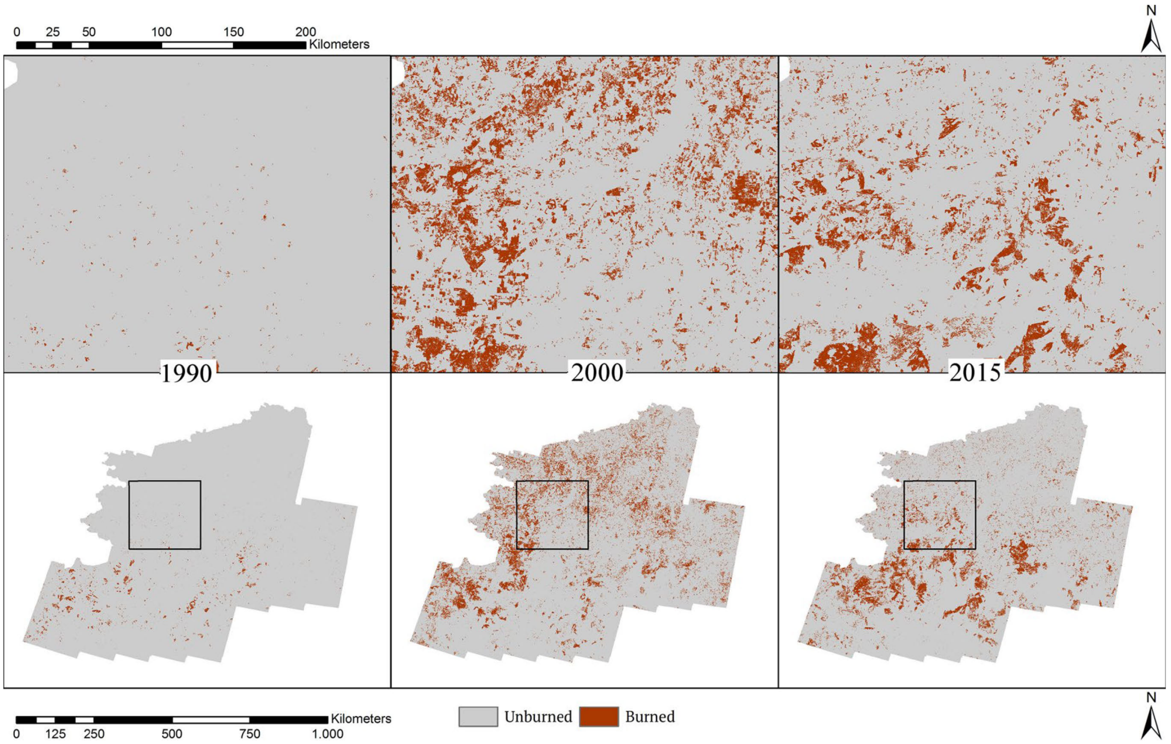

Figure III-3: Burned area maps for the entire study region (bottom row) and exemplary close-ups on a 50,000 km^2 region (top row) for the three time periods 1990, 2000, and 2015.

The proportion of the study region that had burned at least once increased more than sevenfold over the study period, from 1.8 % in ca. 1990 to 13.7 % in ca. 2000, and then slightly decreased to 11.1 % in ca. 2015 (Figure III-3, Figure III-4, and Table III-1). Both the number of patches and average patch area also increased drastically after 1991 (Figure III-4 and Table III-1). All three fire regime attributes showed a moderate but noticeable decline after 2000.

largest among all land-use classes for this period. All three fire regime attributes decreased in major ways on recultivated cropland in the period 2000-2015.

Table III-2: Burned Area Distribution Across Different Land-Use Classes.

	1990		*2000*		*2015*	
	% of burned area	*% of class burned*	*% of burned area*	*% of class burned*	*% of burned area*	*% of class burned*
Cropland	28.04	1.43	49.72	25.07	19.05	7.75
Grassland	68.09	4.27	47.62	15.50	77.57	20.06
Other	3.87	0.78	2.66	3.76	3.38	3.81
Total	-	6.48	-	44.33	-	31.62

Although the fire regime attributes changed similarly for ungrazed, abandoned and permanently grazed steppes, the magnitude of these changes varied markedly (Figure SM III-8). Fire extent in 1990-2000 increased most strongly on ungrazed steppes and around abandoned livestock stations. The same was true for the period 2000-2015. In contrast, the number of fires increased particularly heavily close to points of livestock concentration after 1990, but not after 2000. Average fire size changed in a similar way across all types of steppe. In all periods, burned area and the number of fires were higher on ungrazed steppe than on steppes near active livestock stations.

Land-use change classes	**Change in fire extent, %**		**Change in number of fires, %**		**Change in fire size, %**	
	1990-2000	**2000-2015**	**1990-2001**	**2000-2016**	**1990-2000**	**2000-2015**
Whole region	661	-19	711	-25	17	-12
Permanent cropland	7578	-81	3652	-38	535	-29
Permanently ungrazed steppe	125	43	129	14	-32	14
Croplands abandoned after 1990	2262	10	578	-14	29	-8
Croplands abandoned after 2000	NA	10	NA	-12	NA	32
Croplands recultivated after 2000	NA	-89	NA	-60	NA	-79
Permanently grazed stepppe	407	72	402	-2	-32	5
Abandoned steppe	348	51	354	6	-34	12

Legend		**-20 to 20**	No or little change
<-60	Strong decrease	**20 to 60**	Moderate increase
-60 to 20	Moderate decrease	**>60**	Strong increase

Figure III-5: Relative changes in fire regimes as characterized by three key fire regime attributes (i.e., fire extent, number of fires, and fire size) for the time periods 1990-2000 and 2000-2015.

The proportion of burned area increased substantially with distance from active livestock stations and settlements in all study periods, while this pattern was less pronounced for abandoned livestock stations and settlements (Figure III-6). In 1990, the increase in burned areas was generally small and there was no discernable difference between active and abandoned livestock stations and settlements. This changed in 2000, with a much stronger increase with increasing distance from abandoned livestock stations, while the difference between abandoned and active settlements in 2000 was negligible (Figure III-6). This difference was largest for 2015, when burned area in the immediate surrounding of abandoned livestock stations and settlements was much higher than in livestock stations and settlements that were still active (e.g., 2.9 times at 1 km for the livestock stations, Figure III-6). Overall, the extent of burned area around settlements and livestock stations declined with increasing intactness relative to the Soviet period (Figure SM III-9).

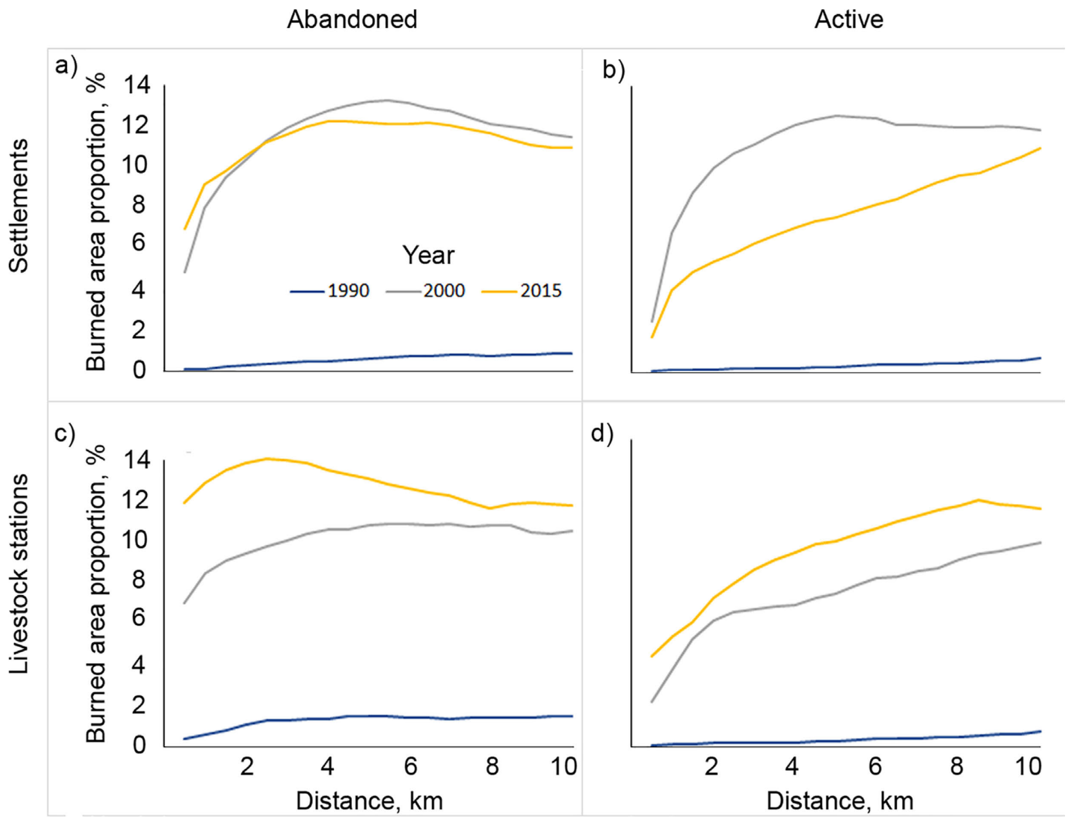

Figure III-6: Differences in fire extent in relation to distance from abandoned (a and c) and active (b and d) settlement (a and b) and livestock stations (c and d) (in 2013) for the periods 1990, 2000, and 2015. Note that livestock stations and settlements that were recorded as abandoned based on recent high-resolution imagery were still in use in 1990.

4 Discussion

Fire plays a key role in temperate steppe ecosystems (Bond and Keeley, 2005; Fuhlendorf et al., 2009), but how land-use change interacts with fire regimes in these regions remains unclear. Our analyses revealed major changes in fire regimes in the steppes of Kazakhstan after the collapse of the Soviet Union. Most notably, we detected a sevenfold increase in burned area and an eightfold increase in fire numbers between 1990 and 2015, likely due to the substantial changes in agricultural management in the post-Soviet era, and specifically the increase in agricultural burning. Second, fire extent and frequency increased particularly on abandoned cropland, likely due to escaped fires from adjacent cropland and due to biomass accumulation because of the massive reduction of livestock grazing. Finally, declining fire control, due to the widespread depopulation of the steppe (Becker et al., 2005; Khaidarov and Arkhipov, 2000), might have contributed to intensifying fire regimes. Overall, our results clearly demonstrate that fire regimes in northern Kazakhstan intensified after the collapse of the Soviet Union, explaining why this region is currently a global fire hotspot (Archibald et al., 2013). We also highlight that fire trends differed substantially among post-Soviet land use, suggesting that context-specific fire management is needed (e.g., enforcing control of agricultural burns and fuel management through locally adapted grazing regimes). Our high-resolution maps of fire activity and land use can provide a template for spatially targeting such policies.

The changes in fire regime we document here are in line with other work. For example, Dubinin et al. (2010) showed a drastic increase in fire extent during the 1990s (0.1 % of area burned in 1989-1991 vs. 10.7 % in 1999-2001) for the Kalmykian Steppes in the south of Russia, similar to what we find in our study area for this period. Likewise, Sukhinin et al. (2004) report an increase in burned cropland and grassland area from 6,470 km^2 in 1996 to 23,312 km^2 in 2002 for entire Russia, which fits to the strong increase we find for the 1990s. After 2000, the moderate reduction in burned area we found fits to the finding by McCarty et al. (2017) for European Russia, Belarus, and Lithuania in the period between 2002 and 2012. Importantly though, all these studies relied on shorter time-frames, smaller study regions, or coarser resolution imagery (e.g., 8-km pixels from AVHRR composites), and were thus often not able to cover the time period of strongest change (i.e., the 1990s), when relying on MODIS data. Our study is, to our knowledge, the first one that reconstructs fine-scale fire patterns and frequencies using Landsat imagery, thereby providing a robust Soviet-period baseline for evaluating post-Soviet changes in fire regimes.

Changes in agricultural management appear to be a key driver of the changing fire regimes we find. Fire regimes changed most strongly on cropland, especially after 1990, most probably due to an increase in intentional agricultural burns that are used to remove excess straw from fields. During Soviet times, straw was used in the large livestock farms, but that is no longer the case due to the collapse of livestock numbers (Koshim et al., 2018). Agricultural burning is discouraged by authorities in Kazakhstan (Khaidarov and Arkhipov, 2000), because they can contribute to air pollution (Michel, 2005; Stohl et al., 2007), reduce soil fertility and bear the risk of spreading to neighboring areas (Moreira et al., 2011; Rabin et al., 2015). Despite that ban, stubble burning is still widespread across the entire former USSR (McCarty et al., 2017). In Kazakhstan, as elsewhere in the former Soviet Union, governmental law enforcement was particularly poor in the 1990s (Holmes, 2009; Semukhina, 2018), when we find the strongest increase in fire intensity on cropland (Table III-2). Finally, we observed fewer fires around settlements than around former livestock stations (Figure SM III-9), probably due to higher fire suppression and fire management (in early stages of fires) close to settlements.

After 2000, we find an overall reduction in fire activity in our study area, again almost exclusively attributed to reduced fire intensity on cropland. On the one hand, the generally stabilizing institutional situation, as well as the emergence of private farms (B. R. Hankerson et al., 2019) with an interest in fire control both might have led to decreasing agricultural burns after the 1990s. On the other hand, the organizational and economic consolidation of the agricultural sector in Kazakhstan, bringing about substantial technological change, might have contributed to the patterns we found. For example, an ongoing replacement of Soviet harvesting technology with modern combine harvesters, that mulch and spread straw, diminishes the need to burn straw on cropland (Source: own field observation).

On grasslands, both natural steppes and abandoned croplands, fire intensity also increased after 1990 but, importantly, did not decrease after 2000. Grazing ceased over vast grassland areas in the study region, and the partial or full abandonment of livestock stations was directly correlated to an increase in burned area and fire frequency. A potential explanation for this pattern is fuel accumulation in the absence of grazing, which has been shown for the ecologically similar North American prairies (Collins and Smith, 2006; Fuhlendorf et al., 2009). For the Eurasian steppe belt, the direct link between the decline in grazing and increasing fire frequency and extent was first suggested by Dubinin et al. (2011), although using extremely coarse-scale data for both fire and livestock. Our study provides the first spatially-detailed evidence for the possible existence of such a link, as our analyses clearly highlight that intensification of fire regimes increased with an increasing level of dismantling of livestock infrastructure, and closer to those points of livestock concentration that were most strongly abandoned (Figure III-6). This link is further corroborated by fine-scale, field measured changes in vegetation composition and grazing pressure indicators (Freitag et al., In Preparation). Likewise, fire regimes intensified on abandoned croplands (Figure III-5), where biomass is no longer removed and is therefore likely to enable more and hotter fires (Brinkert et al., 2016).

Unlike in cropland areas, burned area and fire frequency further increased after 2000 in steppes and abandoned cropland. The likely explanation for these increases is that fuel accumulation takes time, and therefore a time delay between abandonment of grazing or cropping and fire intensity responses could be expected. The effect of intensifying fire regimes also took longer to manifest around settlements than around livestock stations, possibly because livestock husbandry ceased first, and outmigration followed later (Lambin et al., 2013). Finally, with the general depopulation of remote rural areas (Becker et al., 2005; Meyfroidt et al., 2016) this might have resulted in progressively decreasing fire control, such as ploughing of strips along road side verges or around arable fields (Khaidarov and Arkhipov, 2000), especially in those communities suffering substantial outmigration.

An alternative explanation for the intensifying fire regimes we find could be changes in climate (Loboda et al., 2012), which is the case in many world regions (Rocca et al., 2014; Vannière et al., 2008). This explanation seems highly unlikely in our study for three reasons. First, time series of climate parameters that have been linked to fire risk, such as rainfall, aridity, or hot temperatures (Alvarado et al., 2017; Argañaraz et al., 2015; Syphard et al., 2017) do not show noticeable trends over the time period we assessed (de Beurs and Henebry, 2004) and do not align well with trends in fire regime indicators (Figure SM III-10). Second, possible changes in climate do not explain the diverging trends we find in relation to major land-use classes in the region. Third, climate change would also not explain the stark patterns we identify away from points of livestock concentration as well as in relation to the degree of abandonment of livestock stations and settlements.

Our analyses generated several novel datasets, including the first Landsat-based burned area maps for northern Kazakhstan, addressing the need to move to higher resolutions to reliably map fire in steppes (Hall et al., 2016; Hantson et al., 2013; Zhu et al., 2017). Overall accuracies of our maps were high (>90 %), but the producer's accuracies for the burned class were sometimes lower, suggesting that some burns were missed and that our fire maps are conservative. The accuracies were also somewhat lower in earlier periods, probably due to lower image availability (Kovalskyy and Roy, 2013), aggravated by cloud contamination. To remedy low data availability, we used three-year composites, but this could mean that some burned patches may consist of several individual fires that happened in different years (and thus increased fire size). A final limitation to mention is that we could only approximate the areas grazed around livestock stations, as we did not have exact livestock numbers for all stations and settlements, and because herders manage the livestock in relation to available forage and water resources. In reality, grazing pressure will thus vary depending on daily travel distances and grazing patterns of herders and their stock. Including these patterns, for which no data exist at present, would likely strengthen the analyses and the corroboration of the link between grazing and fire we postulate here.

Overall, our analyses revealed marked changes in fire regimes, with generally increasing fire intensity, after the breakdown of the Soviet Union, explaining why this region is now a global fire hotspot. These trends appear to be strongly related to agricultural land-use change, suggesting fire management and land-use policies should be integrated to manage fire risk and active fires. Specifically, regarding croplands, the monitoring and control of agricultural burns should be increased and local authorities should raise awareness among farmers about the possibly harmful effects of these management practices. Regarding abandoned croplands and grasslands, adequate management can decrease fire hazard (Munroe et al., 2013). A reduction of fuel load could be achieved by reviving Kazakhstan's pastoral livestock sector (Hankerson et al., 2019; Preston et al., 2003), a vision that has recently been formulated by the Kazakh government (Ministry of Agriculture of the Republic of Kazakhstan, 2018). In addition, restoring populations of wild grazers such as Kulan (*Equus hemionus kulan*), Przewalski's horse (*Equus ferus przewalskii*) (Bahloul et al., 2001), or saiga antelope (*Saiga tatarica*) (Singh and Milner-Gulland, 2011), could help decrease fire hazards as well as encourage natural restoration of steppes and large mammal conservation (Fuhlendorf et al., 2009). More broadly, our study highlights that the interpretation and management of fire regimes must consider land-use context, and more generally the complex social-ecological interactions in steppes (Chen et al., 2018). Integrating remote sensing observations with land-use data can accordingly provide spatial context for understanding social-ecological interactions not only on the Eurasian steppes, but also in in other grassland biomes around the globe.

Acknowledgements

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Supplementary Material

Text SM III-1: Landsat composite pre-processing

We downloaded all available Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) Level-1 data from the Landsat Collection 1 of the United States Geological Survey (USGS) archive for our study area for three study periods: 1989-1991 (588 images), 1999-2001 (351 images) and 2014-2016 (2598 images). We used all images from the snowless period (April 1 until October 31). We then used the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE, Frantz, 2017) for automatic cloud and cloud shadow detection, masking SLS-off stripes, radiometric correction, and geometric homogenization of all images in order to create gap-free composite metrics for our study area. We also used FORCE to derive spectral metrics from the resulting surface reflectance time series (Frantz, 2018). Specifically, we derived minimum, maximum, mean, standard deviation, quartiles (25, 50 and 75 percentiles), range, skewness and kurtosis for each of the six optical Landsat bands, as well as for the Normalized Burn Ratio (NBR) and Soil Adjusted Vegetation Index (SAVI). This yielded a set of 75 spectral metrics for each pixel for each time period, which served as the input for our burned area mapping.

Text SM III-2: Burned area mapping

Training and validation data – We used Google Earth Engine to collect reference data for burned and unburned areas. We visually inspected every monthly Landsat Normalized Burn Ratio-Thermal (NBRT) composite (Holden et al., 2005) and the MODIS burned area product (MCD64A1, available from 2000) to find burned scars, that could be seen from both products. We considered areas that had low NBRT values (visually identifiable as dark spots) and a shape typical for the fire scars (Figure SM III-1 and Figure SM III-2). To avoid confusion between spectrally similar burned areas and open Chernozem soils of plowed fields we collected reference data only from partially burned agricultural fields that resembled the geometrical pattern of agricultural burning as seen from high-resolution imagery on Google Earth, similarly to Hall et al. (2016). We also controlled for other confusion with other similar events such as floods by checking pre-fire and post-fire composites, when data availability allowed, and the season of the event. For example, floods typically happen in spring in the region, are detectable for no longer than a month and rarely occur in summer (Spivak et al., 2004). We then digitized reference polygons within fire scars. We also collected reference polygons for water, cropland, forest, urban, steppe, and bare soil, taking care that the area had never burned in our observation period. We merged these classes into one “unburned” class, having one reference dataset for burned and one for unburned areas for each of the study periods (i.e. 1990, 2000, and 2015). We randomly divided the set of reference polygons into equally large datasets for training and validation, for each of the three time periods. We then drew 5-10 random points per polygon, depending on polygon size, with a minimum distance of 45 m (more than Euclidean distance for 30 m pixel) between them to avoid pseudo-replication. We derived all 75 metrics values at each point’s location and trained a random forest model to detect burned areas.

<u>Accuracy assessment –</u> After training our random forest model, we classified the spectral metrics to produce a burned vs. unburned area map for each time period. We used the second part of the reference dataset after calculating class inclusion probabilities to ensure area-adjusted accuracy assessment. To ensure rigorous accuracy and area estimation, the class inclusion probabilities were determined through a randomization in sample selection design whereby the probability of every unit selection was known (Olofsson et al., 2014). Inclusion probabilities can be calculated using the number of reference points in a given class and the area proportion of that class in the map. We allocated the number of validation points proportionally to the respective area of that class (Table SM III-1). This design resulted in balanced user's, producers' and overall accuracies.

User's accuracies for the unburned class ranged between 94.9 % and 99.1 % and between 75.3 % and 87.6 % for the burned class. Producer's accuracies were between 66.0 % and 78.1 % for burned class and between 95.7 % and 99.5 % for the unburned class.

<u>Comparison to MODIS burned area product –</u> Comparing our Landsat-based map for 2015 with the MODIS burned-area product for the same year (Figure SM III-2), using independent validation points highlighted that our map outperformed the MODIS map, which had an overall accuracy of 90.9 %, and a user's accuracy of the burned class of only 43.6 %. Burned area detected by MODIS was 20 % lower than the burned area detected by our Landsat-based algorithm (cf. 16 % in (Zhu et al., 2017) for boreal Eurasia with our study region included). Please, note that we compared map areas detected as burned without error-adjustment, as inclusion probabilities were calculated for Landsat data.

Table SM III-1: Validation of the burned area maps. Confusion matrices for 1990, 2000, and 2015.

1990		Reference		
		Fire	No fire	Sum
Classification	Fire	1,395	458	1,853
	No fire	720	8,2508	83,228
	Sum	2,115	82,966	85,081
2000		Reference		
		Fire	No fire	Sum
Classification	Fire	13,123	3,602	16,725
	No fire	4,262	79,221	83,483
	Sum	17,385	82,823	100,208
2015		Reference		
		Fire	No fire	Sum

Classification	Fire	5,685	804	6,489
	No fire	1,599	44,467	46,066
	Sum	7,284	45,271	52,555

Text SM III-3: Analyzing grazing intensity

The Soviet topographic maps were issued between 1970 and 1988 (with one exception, a map sheet that was produced in 1962 already and never updated). Issue dates were given at the map sheet margins. Ca. 90 % were updated and published in the period 1981–1985. Satellite images used to evaluate the contemporary situation were mostly from 2010 to 2014, with a peak availability in 2012. For the Bing images, information an image was taken was extracted from http://mvexel.dev.openstreetmap.org/bing/. For the Google images, the date was read from the "imagery date" button in Google Earth. Below are a number of examples to document the identification process of the abandonment of settlements.

Figure SM III-3: Abandoned agriculture in Kostanay region of northern Kazakhstan in late April 2015. Abandoned livestock station (left photo). Abandoned crop field (on the right hand side) next to an active one (right photo). Grass species common for steppe are dominant in successional vegetation.

Figure SM III-4: Almost completely abandoned settlement; only two intact, roofed houses remain, roads only partly used (Google Earth, view altitude: 1 km). Summer 2014.

Figure SM III-5: Intact settlement, no derelict houses visible, large cattle stables managed at northeastern end of village (Google Earth, view altitude: 1 km). Summer 2016.

Figure SM III-6: Former livestock station (“Zimovka”) in summer 2013. No signs of current use, no intact buildings, road overgrown and unused, no corrals visible (Google Earth, view altitude: 1 km).

Figure SM III-7: Used “Zimovka” (livestock station), summer 2015. Buildings maintained, road network well in use, corrals (with dark surface due to dung deposition) visible (Google Earth, view altitude: 1 km). Different corrals are used here; the small quadratic ones close to the stable are for keeping sheep safe overnight, the large, circular one is used to concentrate horses for milking and veterinary treatment.

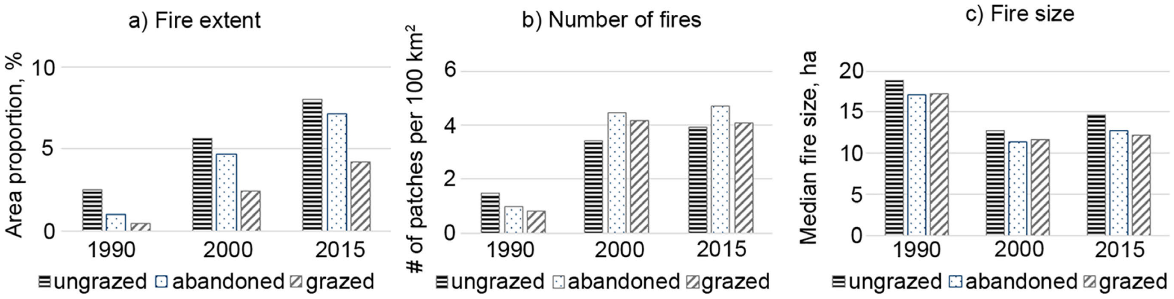

Figure SM III-8: Changes in fire regimes according to three fire traits for 1990-2000-2015 on ungrazed steppe (grasslands > 10 km away from livestock stations and settlements), near (< 5 km) abandoned livestock stations, and active livestock stations (< 5 km). We excluded a buffer between 5 and 10 km away from the livestock stations from this analysis because of a highly diverse grazing intensity in these areas (Hankerson et al., 2019).

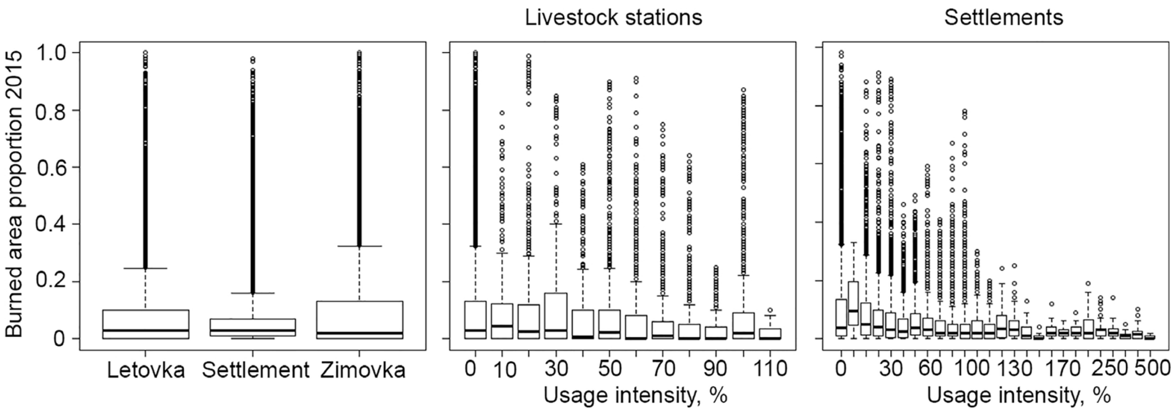

Figure SM III-9: Difference between burned area extent in 10-km buffers around settlements and summer (letovka) and winter (zimovka) livestock stations and in relation to a level of abandonment or intensification.

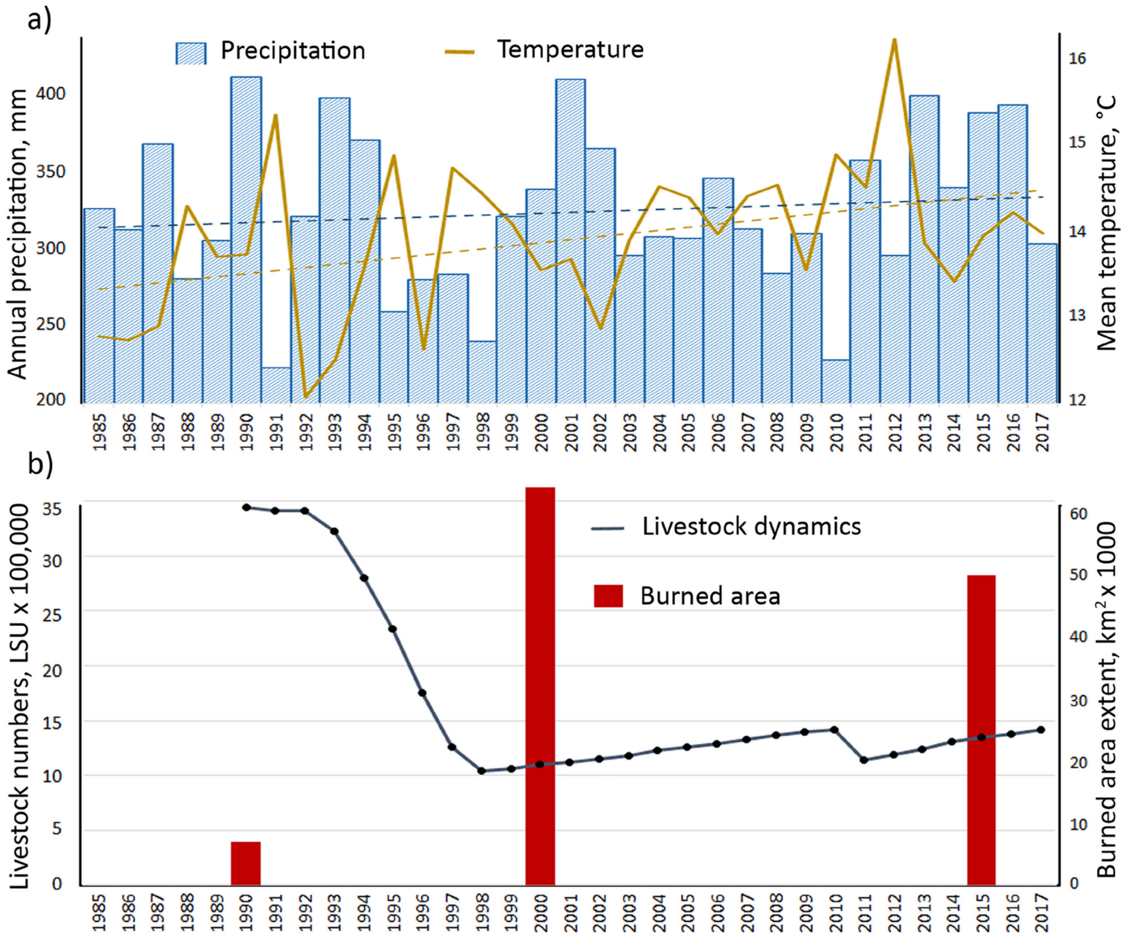

Figure SM III-10: Total annual precipitation and mean temperatures for April to October aggregated from rayon-level monthly the Climatic Research Unit (CRU) data (Harris et al., 2014), and their respective linear trends (a) do not seem to explain the changes in burned area after the collapse of the Soviet Union. Decrease in livestock numbers in this period had far larger magnitude (b, rayon-level data from official statistics (KazStat, 2019), Livestock Units (LSU, Eurostat, 2013) are calculated as Horses + 0.1 * (Sheep and goats)+ 0.8 * Cattle). Moreover, substantial increase in burned area was a result of intentional burning of crop residue, which cannot be linked to climate change.

Chapter IV:
Annual Landsat time series reveal post-Soviet changes in grazing pressure

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Abstract

Temperate grasslands are globally widespread, play an important role as carbon storage, and harbor unique biodiversity. Livestock grazing is the most widespread land use in temperate grasslands, and understanding the impact of grazing on grassland ecosystems is therefore important. However, monitoring grazing pressure and how it changes is hampered by a lack of adequate tools. The Eurasian steppe belt, extending from Eastern Europe to China has experienced marked changes in grazing pressure. Most notably, livestock numbers in the steppes of Kazakhstan and Russia declined by up to 80 % after the breakdown of the Soviet Union in 1991, yet how this impacted spatial patterns of grazing pressure is unclear. To address this research gap, we used all available Landsat data from 1985 to 2017 together with extensive ground reference data on grazing pressure to evaluate a broad range of spectral-temporal metrics regarding their ability to capture grazing pressure. While Tasseled Cap-based disturbance indices performed best, combining all spectral-temporal metrics in a binary random forest classification yielded a grazing class membership probability that strongly outperformed all individual metrics. This new index of grazing pressure correlated well with a range of field-based grazing indicators (e.g., number of dung piles, herbaceous biomass) and yielded highly plausible spatial patterns of grazing pressure. We used this index to reconstruct annual changes in grazing pressure across our 360,000 km² study region, and used LandTrendr time series segmentation to identify trends in grazing pressure. Aggregated grazing pressure followed closely known trends in total livestock numbers over the time period we studied. The spatial footprint of heavy grazing was very large before 1991, but decreased by 73 (±2) % until 2017. This now leaves large areas virtually ungrazed, even in close vicinity to settlements and agricultural areas, and despite a recent recovery of livestock numbers. Our analyses uncovered previously unknown hot-spots of heavy grazing during Soviet times (e.g., around watering points). Our findings suggest potential for a further revival of the livestock sector as well as for the restoration of steppe ecosystems. More broadly, our study highlights how the Landsat archive, in combination with field data on grazing, can be used to map grazing pressure reliably across large areas and over long time spans.

1 Introduction

Grasslands cover large areas globally, harbor a rich and diverse flora and fauna (Suttie et al., 2005), and contain about 30 % of the global carbon stored in soils (Anderson, 1991). Temperate grasslands have historically undergone substantial land-use change, both in terms of conversion to cropland, and in terms of intensifying livestock grazing (Goldewijk, 2001; Laycock, 1987). These changes have been particularly pronounced in the steppes of Eurasia, primarily because of their high agro-ecological suitability for cropping and grazing and low costs of conversion to croplands (Prishchepov et al., 2020). Historically these steppes were grazed by large ungulates, such as Kulan (*Equus hemionus*) and Saiga antelope (*Saiga tatarica)*, and were subject of nomadism. However, since the 19th century, numbers of wild ungulates have decreased drastically (Bekenov et al., 1998; Robinson and Milner-Gulland, 2003) and thus, grazing pressure mainly comes from domestic livestock (Kerven et al., 2006).

The rise and fall of the Soviet Union brought about major changes in grazing systems across the Eurasian steppe. The establishment of the collectivized state farms from 1929 to 1933 (Olcott, 1981) and plowing of steppes across vast areas during Khrushchev's Virgin Lands campaign in 1954-1963 (McCauley, 1976) increased grazing pressure of domestic livestock on remaining grasslands substantially. Although a semi-nomadic system of livestock keeping distributed grazing pressure between winter and summer pastures (Kerven et al., 2006), the Soviet period saw very high grazing pressure (Robinson et al., 2003). This changed after the breakdown of the Soviet Union in 1991, when livestock numbers dropped by up to 80 % in Kazakhstan as a whole (KazStat, 2019). At the same time, the remaining livestock was increasingly concentrated around villages, because remote livestock outposts were no longer maintained (Alimaev et al., 2008). This suggests massively declining grazing pressure across large steppe areas (Hölzel et al., 2002), yet also increasing pressure locally. However, the spatial patterns of these changes remain elusive.

This is unfortunate as both overgrazing and undergrazing lead to unwanted environmental outcomes (Follett et al., 2001). For instance, overgrazing can cause soil degradation, biomass reduction, and desertification (Hilker et al., 2014; Wang et al., 2014). At the same time, low grazing pressure increases dry biomass, thus increasing fuel for wildfires (Dubinin et al., 2011; Van Auken, 2000). Intensifying fire regimes, in turn, can lead to increased carbon emissions, soil degradation, and nutrient leaching (Pellegrini et al., 2017; Stohl et al., 2007). Thus, the spatial distribution of grazing pressure plays a crucial role for healthy steppe ecosystems (Kamp et al., 2016). Understanding the spatial footprint of grazing, and how it changes, is therefore important.

Grazing pressure can be assessed directly in the field, or indirectly via land-use modeling (Hankerson et al., 2019; Robinson et al., 2014). However, both approaches rely on livestock statistics, which can be unreliable for post-Soviet countries (Burkitbayeva and Oshakbayev, 2015; Kraemer et al., 2015), and both approaches cannot provide detailed spatial patterns of grazing across larger areas. Remote sensing can fill this gap, but separating grazing impact from other vegetation dynamics (e.g., due to fire or climate variability) is challenging (Kamp et al., 2016; Wright et al., 2009; Zhao et al., 2011). Past attempts to assess grazing pressure in steppe have for this reason typically relied on temporally-detailed time series from broad-scale sensors. For example, MODIS time series (250 m/500 m) have been used to assess grassland management change using phenology metrics (Estel *et al.*, 2015; Heumann *et al.*, 2007; Jamali *et al.*, 2015). Similarly, Propastin *et al.* (2008) mapped hotspots of vegetation change across Central Asia using 1-km AVHRR time series, although this study did not separate croplands from grasslands. Approaches that utilize such broad-scale sensors, however, require very dense time series and are unable to detect the fine-scale spatial heterogeneity in vegetation and grazing impact that characterizes Eurasian steppes, especially before 2000.

The Landsat image archive provides high-resolution imagery with a long enough record to separate the effects of grazing, phenology, and inter-annual climate variations on vegetation (Vogelmann et al., 2016). It extends back for more than three decades to Soviet times, although lacking temporal details in our study area (Dara et al., 2018; Kovalskyy and Roy, 2013). Previous work has highlighted the potential of Landsat to map grazing pressure in steppes. For example, Landsat imagery revealed that a grazing ban helped to revert grassland degradation in China (Li et al., 2013). Likewise, Lehnert *et al.* (2015) compared different sensors, including Landsat, to highlight that grassland dynamics on the Tibetan plateau can be mapped reliably. Landsat imagery was also used to assess spatial patterns of steppe degradation in Central Asian deserts (Karnieli et al., 2008). Yet, to our knowledge no study has used the depth of the entire Landsat archive to map grazing-related changes in steppe vegetation from Soviet times until today.

Two main methodological challenges likely explain this. First, the region suffers from relatively scarce Landsat imagery from the 1990s (Dara et al., 2018; Wulder et al., 2008), which are a real obstacle for traditional time series analyses. Yet, new approaches that use the entire archive, such as pixel-based compositing and spectral-temporal metrics, have now become available to help overcoming limitations due to data gaps (Griffiths et al., 2013; Hermosilla et al., 2015). Second, a key challenge for assessing grazing pressure is to find metrics that are sensitive to changes therein (Ren et al., 2018). A number of candidate metrics exist, including Tasseled Cap indices, vegetation indices, vegetation fractions from spectral mixture analysis (Hostert et al., 2003; Karnieli et al., 2008; Sonnenschein et al., 2011), or a specifically developed grassland disturbance index (DI, De Beurs et al., 2016). Also, class membership probabilities can sometimes be more informative for mapping gradual change processes (Dara et al., 2018; Yin et al., 2018). It is unclear though, which of these indices capture grazing pressure in Eurasian steppes best.

Once potentially promising indicators are found, trend analyses can capture changes in vegetation (Bullock et al., 2018; Sonnenschein et al., 2011; Vogelmann et al., 2016). Trajectory-based analyses on segmented time series, such as performed by LandTrendr (Kennedy et al., 2010), are particularly promising. LandTrendr uses temporally aggregated spectral input, such as spectral indices, to detect both abrupt changes such as forest disturbances (e.g., Nguyen et al., 2018; Pflugmacher et al., 2014; Senf et al., 2015) or cropland abandonment (Dara et al., 2018; Yin et al., 2014), as well as gradual changes, such as post-fire recovery (e.g., Frazier et al., 2015; Pflugmacher et al., 2014). Provided there are spectral indicators sensitive to grazing pressure, LandTrendr should be well-suited to map the spatial footprint of grazing, and thus potentially steppe degradation and recovery.

Our overarching goal was to evaluate the suitability of trajectory analyses to reconstruct changes in grazing pressure in Eurasian steppes based on the Landsat archive. We focused on a 360,000 km² study region in the north of Kazakhstan, where widespread abandonment of pastures occurred after the breakdown of the Soviet Union. Generally, our approach consisted of (1) assessing the performance of a range of spectral-temporal metrics, as well as an aggregate class-probability-based metric, for capturing differences in grazing pressure; (2) to then calculate the best-performing metrics across our time series; to finally (3) use LandTrendr to map trends in grazing pressure. As reference information, we used a unique field dataset on grazing pressure (n = 843) and a large dataset on changes in livestock grazing infrastructure (n = 3,373).

dataset on changes in livestock grazing infrastructure (n = 3,373). Specifically, we ask:

1. Which metrics derived from Landsat imagery capture grazing pressure best?
2. Do Landsat-based trajectory analyses capture changes in grassland condition due to changing grazing pressure?
3. What were the spatiotemporal patterns of changes in grassland condition after the breakdown of the Soviet Union?

2 Material and Methods

2.1 Study region

Our study area is the steppe and semi-desert belt of northern Kazakhstan (Figure IV-1). The climate there is characterized by cold and snowy winters, and hot and dry summers, with temperatures ranging from -50°C to +40°C. Precipitation varies from < 200 mm in the south to 350 mm in the north. Grasses (*Stipa*, *Festuca)* and wormwood (*Artemisia*) dominate the vegetation in the area. Kastanozems of variable humus content are most widespread. The most fertile Chernozems soils are located in the less arid northern part (Beznosov and Uspanov, 1960).

Agricultural land prior to the breakdown of the Soviet Union was mainly used for growing cereals in the northern part and for livestock grazing in the southern part. After 1991, more than one third of all croplands were abandoned and livestock numbers declined by two thirds. In the 2000s, some recultivation (ca. 15 % of abandoned croplands) and a moderate recovery of livestock numbers occurred (+30 % from the 1998 level) (Baumann et al., In review; Kamp et al., 2011). Livestock owners today use some of the remaining Soviet livestock infrastructure, such as livestock stations and wells, but most of the livestock is now kept around villages (Kamp et al., 2011; Kerven et al., 2006). Additionally, grazing also occurs along rivers and roads.

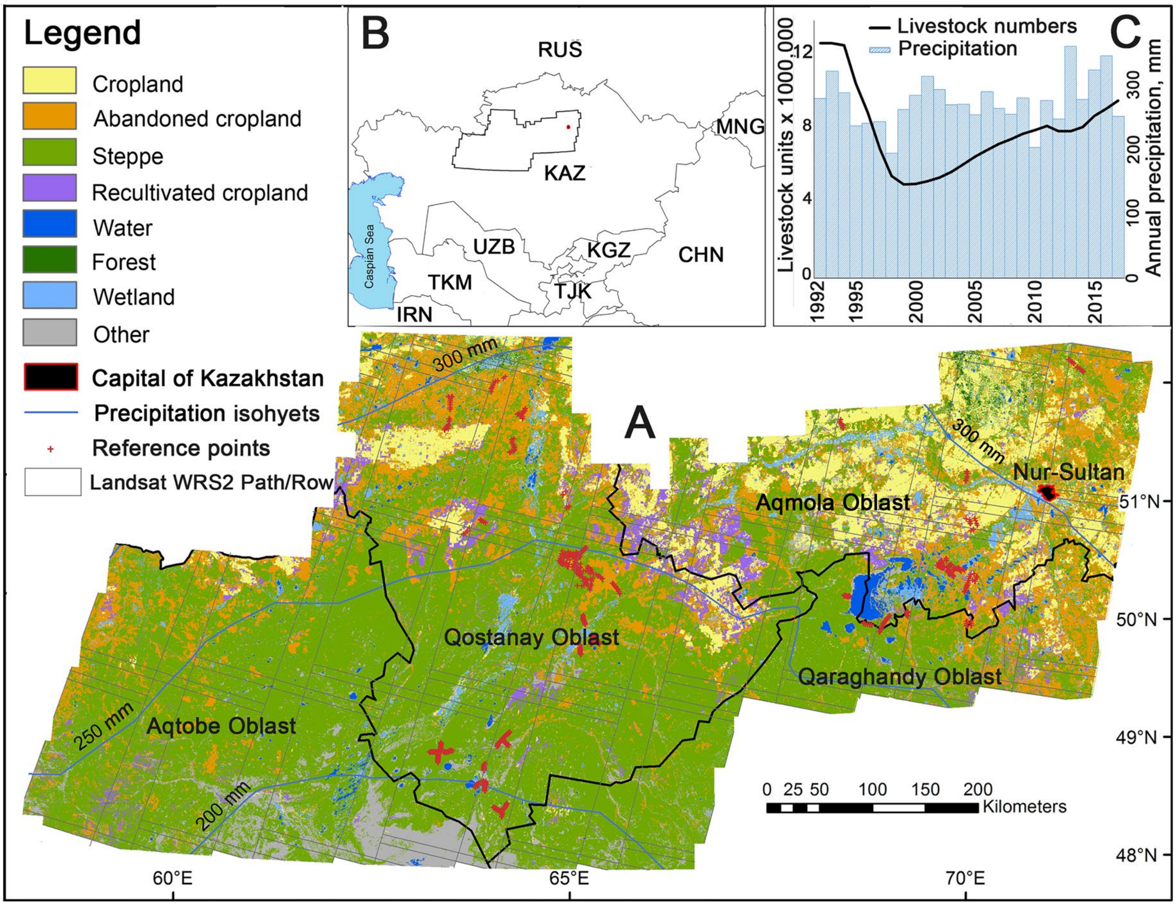

Figure IV-1: A: Study area with Landsat-based land-cover/change classes (Baumann et al., In review). The Abandoned croplands class highlights croplands that were abandoned after 1991. Recultivated croplands were abandoned before 2000 but brought back into production thereafter. The class 'other' contains bare soil and impervious surfaces. Isohyets show the precipitation gradient. Inset B shows the location of the study area in Central Asia (CHN = China, IRN = Iran, KAZ = Kazakhstan, KGZ = Kyrgyzstan, MNG = Mongolia, RUS = Russia, TJK = Tajikistan, UZB = Uzbekistan). Inset C shows total annual precipitation and changes in livestock numbers, expressed as livestock units based on country-level statistics on cattle, sheep, goats, and horses (Source: FAOSTAT, 2017).

2.2 Datasets used

We used all available Landsat TM, ETM+, and OLI imagery from the snowless season of each year from 1985 to 2017. We used Tier-1 surface reflectance imagery, atmospherically corrected with LEDAPS (for TM and ETM+) and LASRC (for OLI) as available from USGS via Google Earth Engine. Clouds, cloud shadows and snow were masked using CFMASK (Foga et al., 2017).

To assess the accuracy of the remote sensing analyses, we used data from 843 vegetation plots of 10x10 m each (Table IV-1). We collected these vegetation data across the study area along a gradient of grazing pressure and across all major ecozones (productive steppe, dry steppe, and semi-desert) in 2009, 2010, 2015, and 2016. Field data were collected independently from each other, meaning each point was visited once. We used a systematic sampling design to account for a possible sampling bias (Congalton and Green, 2008). Field observations from every year and a random sampling design could have increased reliability of our area estimates, however, the latter was not possible due to logistical reasons, and the ground data from early years of our study period do not exist to our best knowledge. At each plot, we recorded the cover of all plant species, total vegetation cover, bare ground, and vegetation height. We allocated the vegetation plots to three classes of grazing pressure ('heavily grazed', 'moderately grazed' and 'ungrazed') for the analysis. The classification was based on a visual, *in situ* assessment, and the final decision was made based on the plant species composition, cover of bare ground, live and dead biomass and density of dung piles. Plots were classified as moderately grazed if clear signs of grazing were visible, such as partially defoliated plants, few dead biomass and dung piles, while a high cover of bare ground and characteristic plant species (e.g. annuals, certain *Artemisia* species) indicated heavy grazing (Figure IV-2). We also collected biomass by cutting all herbaceous biomass at five quadrats of 0.1 m² randomly placed within 335 independently sampled plots. We weighed biomass after drying for 48h at 70°C (for further details of vegetation, biomass and dung pile sampling see Brinkert et al. (2016). In addition, at these 335 plots, we counted the dung piles of sheep, cattle and horses along a strip transect of 100m length and 2m width. This transect was centered on the plot (i.e. we always walked 50m away from the plot in eastern and western direction). The dung estimate hence characterizes the grazing intensity in the immediate vicinity of the plot, considering that plots were spaced at least 2 km apart from each other (Laing et al., 2003).

Table IV-1: Summary of field data collected during field campaigns in the period 2009 to 2016, including the sampling methods, number of samples, and specific time period covered by our different field datasets.

Type	*Sampling method*	*Time period*	*# of plots*
Levels of grazing pressure	Expert-based classification in the fields in 10x10 m² vegetation plots. Three levels of grazing (high, moderate, low) were distinguished based on a visual assessment of signs of grazing, dung density, species composition, total vegetation cover, bare ground, and vegetation height.	2009, 2010, 2015, 2016	843
Biomass estimation	All herbaceous biomass was harvested in plots consisting of 5 quadrats of 0.1 m² each, dried, weighted and averaged.	2015, 2016	335
Dung piles counting	Dung piles of sheep, cattle and horses were counted on transects of 100m x 2m, centered on a 10x10 m² vegetation plot. Dung pile values were averaged.	2015, 2016	335

As additional indicators for grazing pressure, we digitized winter and summer livestock stations ('*zimovkas*' and '*letovkas*' in Russian) and settlements (hereafter jointly referred to as 'livestock concentration points') from 1:100,000 Soviet topographic maps from the midlate 1980s (VTU GSh, 1989). *Zimovkas* and *letovkas*, across the former Soviet Union, are outposts on summer or winter pastures, where livestock is concentrated that does not need to be kept in sheds overnight. The stations usually consist of one to three houses or tents ('yurts') for shepherd accommodation and a corral for livestock shelter during the night. We checked if these livestock concentration points were still actively used based on recent high-resolution imagery from Google Earth (mostly from 2010 to 2014, with peak availability in 2013). We assigned a usage intensity index from 0 to 100, based on the share of intact infrastructure. This can be identified reliably from satellite imagery as active corrals, where livestock is kept overnight, accumulate dung and have animal tracks leading to them, while abandoned infrastructure collapses quickly in the area as they are predominantly built from clay bricks.

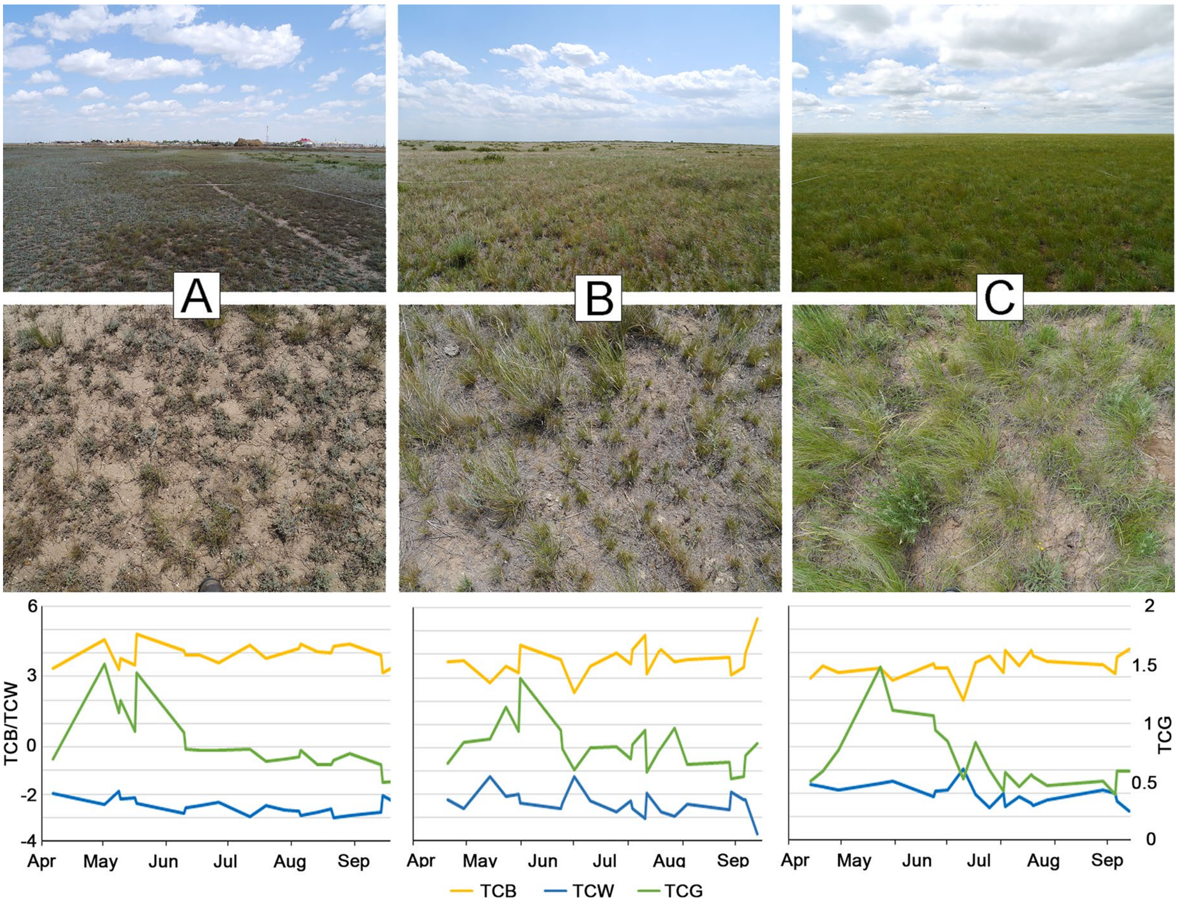

Figure IV-2: Examples of vegetation plots showing heavily grazed (A), moderately grazed (B), and ungrazed (C) steppes from the field campaign in June 2015. The bottom row shows the respective time series of Tasseled Cap brightness (TCB), greenness (TCG), and wetness (TCW) values in the snowless period of that year. Grazed plots demonstrate generally higher TCG values than the ungrazed plots. Note also that grazed plots, and particularly heavily grazed plots have an earlier greenup and a distinct second vegetation peak early in the season.

As ancillary data, we used a Landsat-based land-cover/change map (Baumann et al., In review), and a soil map (Beznosov and Uspanov, 1960). We also used official rayon (= district)-level time series on the number of cattle, horses, sheep, and goats from the Statistics Agency of the Republic of Kazakhstan (KazStat, 2019) from 1990 to 2017, and aggregated them to livestock units according to EUROSTAT conversion factors (horses = 1, cattle = 0.8, sheep and goats = 0.1 units, Eurostat, 2013). Comparing livestock numbers to those available at FAOSTAT for the whole country suggests our study area is representative for the entire Kazakh steppe. We used an aridity index based on the WorldClim2 Global Climate Data (Fick and Hijmans, 2017; Trabucco and Zomer, 2018). Finally, we acquired monthly rayon-level precipitation and temperature data from the Climatic Research Unit (CRU, Harris et al., 2014) and aggregated them into annual mean temperature and total precipitation time series for 1985-2017.

2.3 Landsat spectral-temporal metrics

We based our analysis on a set of annual spectral-temporal metrics from Landsat for the period 1985-2017 (Figure IV-3). We calculated these metrics in Google Earth Engine (Gorelick et al. 2017), which we accessed through the python interface. To do that, we selected for each year all available Landsat images between April and October from all three sensors (TM, ETM+, OLI), applied the coefficients by Roy et al. (2016) to OLI images to account for sensor differences between OLI, TM and ETM+ (Oeser et al., 2017), and masked out clouds and cloud shadows. We then calculated the Normalized Burn Ratio (NBR), Enhanced Vegetation Index (EVI), Modified Soil Adjusted Vegetation Index (MSAVI) and the three Tasseled Cap components: brightness, greenness and wetness (Christ and Kauth, 1986; Crist, 1985). We applied transformations of reflectance from Landsat bands to calculate Tasseled Cap components following Crist (1985). We then calculated for each pixel the yearly mean, median, as well as 10^{th} and 90^{th} percentile of each metric and downloaded the complete set of metrics for subsequent analyses. We also calculated, offline, three variations of the disturbance index (see below) from normalized median Tasseled Cap wetness, greenness, and brightness. This resulted in a total of 27 metrics per year (four statistical measures times six spectral indices, plus three disturbance indices).

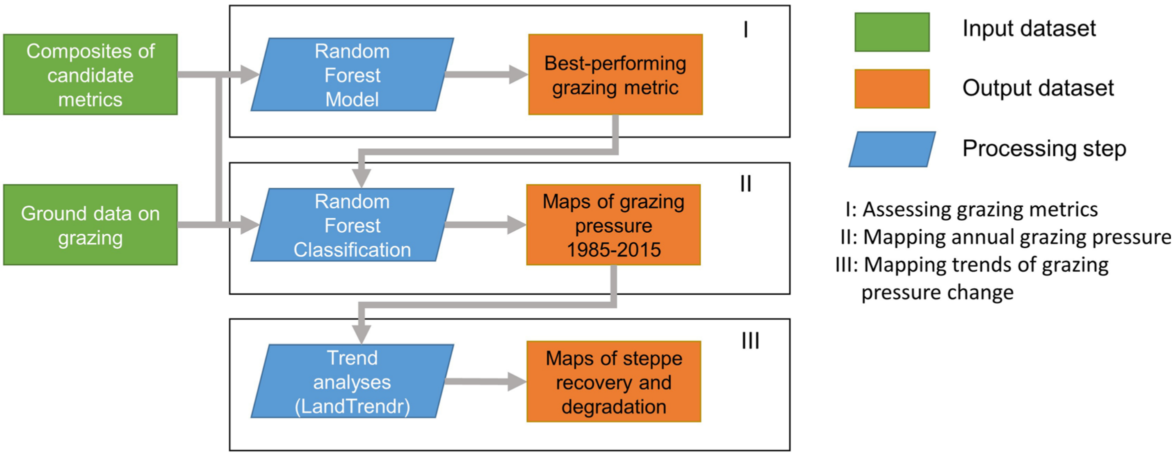

Figure IV-3: Workflow of key inputs, outputs and processing steps to evaluate grassland trends in Kazakhstan in 1985-2015 due to changing grazing pressure divided into three major stages. I: assessing the performance of a range of spectral-temporal metrics, as well as an aggregate class-probability-based metric, for capturing differences in grazing pressure; II: calculating the best-performing metrics across our time series; and III: using LandTrendr to map trends in grazing pressure.

2.4 Measuring grazing pressure

The disturbance indices (DI) assume that Tasseled Cap components (greenness, brightness and wetness) respond in predictable ways after a disturbance and transform these components to maximize this response. The original DI (Eq. 1, Healey et al., 2005) was developed to capture forest disturbances, which are assumed to lead to an increase in brightness and a decrease in greenness and wetness. This index was modified for grasslands (de Beurs et al., 2016), where disturbances are assumed to lead to a decrease in all three Tasseled Cap components (Eq.2). Our study region is characterized by brighter soils in steppe areas (Beznosov and Uspanov, 1960), in contrast to the soils for which the grassland DI was developed. We therefore tested a third, steppe-DI, based on the assumption that grazing leads to an increase in brightness, because herbaceous biomass is reduced and the bare cover increases (Eq.3). We assumed greenness to be higher in grazed areas due to two mutually not exclusive reasons: the first is the resprouting of green leaves, i.e. regeneration of new shoots after a disturbance, such as grazing or fire in perennial plants (Kleinebecker et al., 2011; McNaughton, 1984). This resprouting can possibly be observed in a time series of Tasseled Cap greenness in early June (Figure IV-2) and results in a slightly higher median Tasseled Cap greenness values in our spectral-temporal metrics (see Figure IV-4). Second, grazing reduces dry biomass, which otherwise may reduce the weight of greening in the overall signal.

$$\mathbf{DI_{Healey} = TCB - (TCW + TCG)} \qquad \textit{Equation 1}$$

$$\mathbf{DI_{de\ Beurs} = -(TCB + TCW + TCG)} \qquad \textit{Equation 2}$$

$$\mathbf{DI_{steppe} = TCB + TCG - TCW} \qquad \textit{Equation 3}$$

Prior to calculating the DIs, we normalized all three tasseled cap components to account for the different value ranges of each component (Healey et al., 2005, de Beurs et al., 2016). As the reference for this normalization, we used locations identified as 'ungrazed steppe' in the field. We then used the three resulting normalized components and calculated DI_{Healey} and DI_{steppe} as outlined above. As de Beurs et al. (2016) used stratified reference datasets according to climatic zones, we followed this approach and used ten zones based on the aridity index to calculate standardization datasets for the $DI_{de\ Beurs}$.

To quantitatively rank our metrics in their ability to capture grazing pressure, we used a random forest classifier. Specifically, we used two grazing pressure classes, based on vegetation plots visited in the field: 'heavily grazed' (n = 190) or 'ungrazed' (n = 385). These classes represent the two contrasting ends of the grazing gradient, which allowed for a binary classification. As a result, we can interpret the class membership probability of the class 'heavily grazed' as a proxy for grazing pressure. We used the spectral-temporal metrics derived from years when reference data were collected (i.e., 2009, 2010, 2015, and 2016) for training and cross-validation of our generalized model, as we assumed our reference data not necessarily to represent conditions outside the year when plots were visited. We trained binary ('heavily grazed' vs. 'ungrazed') random forest models for each index individually and calculated overall and class-specific accuracies (including 95 % confidence intervals around them) using a 10-fold cross-validation. For accuracy assessment we generally followed best-practice guidelines (Olofsson et al., 2014). As a second measure, we also trained a random forest model using all 27 metrics and assessed the relative importance (mean decrease in impurity) of our metrics in this model. We used the model that performed best according to a 10-fold cross-validation, which was the model with 150 estimators (i.e., the trees in the forest) without bootstrapping (i.e., all training data were used to build each tree). Based on this, we used the resulting class membership probabilities for the class 'heavily grazed' as an additional grazing metric (hereafter: grazing probabilities).

For the classification, we used the scikit-learn library for python, where class membership probabilities are calculated as the mean probability estimated by all trees for the class, which in turn refers to the fraction of votes for a class by each leaf of the tree. For instance, if 100 out of 150 trees in our model would estimate a probability of a pixel belonging to 'heavily grazed' class as 0.7, and the remaining 50 trees would estimate this probability to be 1, the resulting 'grazing probability' would be 0.8. We then applied this generalized, time-aggregated model to the annual layers of spectral-temporal metrics for years between 1985 and 2017 to derive annual time series of grazing probabilities, as we assumed the model trained on the data from four years to work reliably when projected on other years.

Once all metrics were calculated, we extracted metric values for all vegetation plots for the year in which the plots were surveyed. We created boxplots of metric values for the grazing pressure classes 'heavily grazed', 'moderately grazed', and 'ungrazed' that were originally assigned based on field data. To assess the plausibility of our grazing probability as a proxy for grazing pressure, we visualized probabilities also for an intermediate class 'moderately grazed', which was identified in the field but not used in our classifier. If our grazing probability was a useful proxy of grazing pressure, we would expect grazing probabilities to be intermediate for the moderately grazed class, and probabilities to lay between the two classes 'heavily grazed' and 'ungrazed'. We also compared our grazing metrics using Spearman's rank correlation ρ to herbaceous biomass yield and the number of dung piles per plot counted in the field. Finally, we plotted the best-performing metrics against a range of environmental variables (i.e., soil type, soil texture, annual mean temperature, annual precipitation, mean temperature in the driest quarter, precipitation in the driest quarter, and aridity index) in order to examine whether observed differences were more likely due to differences in grazing pressure or environmental conditions.

Using the dataset of livestock concentration points, we evaluated how our grazing pressure changed away from these points over time. We created concentric buffers of 1 km, 3 km, and 6 km around livestock concentration points and derived the mean of our grazing metrics within each buffer for each year. We then compared how these values changed over time around livestock concentration points with usage intensity < 20 % (N = 2160, close to or fully abandoned, hereafter: 'abandoned'), 20-60 % (N = 591, largely abandoned, hereafter: 'semi-active'), and > 60 % (N = 622, still in use, hereafter: 'active'). Please note that we purposefully used overlapping buffers, as livestock is free-ranging. Thus, the buffers around an active settlement might contain areas adjacent to an abandoned livestock station nearby, and vice versa.

We used a grazing probability threshold of 0.8 (i.e., the threshold that included 98 % of the plots characterized as ‘heavily grazed’) as a conservative measure to estimate the proportion of heavily grazed areas in our annual maps, and we applied this threshold in our accuracy assessment. As we did not have reference data for years prior to 2009, we used the same confusion matrix as for the accuracy assessment of our model, but assuming grazing probability above 0.8 (instead of a standard 0.5 threshold) to represent ‘heavily grazed’ areas. Based on this, we calculated error-adjusted area proportions (including 95 % confidence interval) of overgrazed areas on these maps following best practices (Olofsson et al. 2014).

2.5 Trend analyses to map changes in grazing pressure

We used LandTrendr and our grazing probability metrics to map recovery and degradation trends across our study region in the Kazakh steppe. LandTrendr performs a temporal segmentation by fitting an input time series to form a predefined maximum number of linear trend segments for each pixel. Fitted trends are then divided into descending (disturbances) and ascending (recovery) trends for given parameters, such as duration and magnitude (Kennedy et al., 2010). LandTrendr was originally designed to map forest disturbance, assuming metrics will decrease after a disturbance (e.g., NBR, Cohen et al., 2010; Kennedy et al., 2010). For our grazing probability metric, we assumed positive trends to represent increasing pressure, and negative trends to represent recovery. As we were only interested in long-term trends, we restricted the number of fitted segments to four and allowed only trends longer than four years. We considered trends in grazing probabilities to be significant at $p < 0.05$. Using this parameterization, we mapped grazing pressure change over the entire period 1985-2017. After initial testing, we decided to interpret only trends longer than 10 years, with a change magnitude of > 45 %. Additionally, for recovery trends, we only interpreted trends with an initial grazing probability of > 0.8. This yielded a map of grazing pressure change for the whole study region. To assess how grazing trends varied away from livestock concentration points of different usage intensity, we created concentric 500 m buffers from 0.5 km to 8 km. We then extracted the median magnitude of the longest recovery trends, as well as the median duration, per buffer.

3 Results

Spectral metrics varied greatly in their ability to capture different levels of grazing pressure. When using the metrics individually in our random forest models, overall accuracies ranged between 68 % and 78 %. Median Tasseled Cap wetness outperformed other single metrics, with 78 % overall accuracy, followed by DI_{steppe} (our own modification of the DI). When using all metrics together in one classification, the importance of metrics varied from 1 % (EVI p90) to 16 % (DI_{steppe}) (Table IV-2, Table SM IV-1) and this model had an overall accuracy of 89 %. In this model the class heavily grazed had a user's and producer's accuracy of 90 % and 95 % respectively. We therefore considered grazing probabilities (i.e. the class probability for the class 'heavily grazed' when using all metrics in the classifier as input features) to be the best-performing metric.

Table IV-2: Top-performing grazing metrics based on (a) individual performance in single-metric random forest models, including the 95 % confidence interval (CI), (b) the importance of metrics when using all metrics in one random forest model, (c) correlation with field-surveyed dung piles, and (d) correlation with field-surveyed herbaceous biomass. (TCG = Tasseled Cap Greenness, TCW = Tasseled Cap Wetness, DI = Disturbance Index). Please see Table S1 in the Supplementary Material for performance indicators for all spectral-temporal metrics tested.

Metrics	*Overall accuracy (CI)*	*Feature importance (node impurity)*	*Spearman's ρ for dung piles*	*Spearman's ρ for biomass*
DI_{steppe}	78 (75-81) %	16 %	0.55	-0.32
TCW Median	76 (73-80) %	7 %	-0.46	0.32
$DI_{de\ Beurs}$	73 (70-77) %	3 %	0.02	-0.18
DI_{Healey}	72 (68-75) %	3 %	0.13	-0.23
Grazing probability *	89 (87-92) %	---	0.58	-0.53

** Based on a random forest classification model using all 27 metrics.*

Tests of our grazing metrics against field variables on grazing pressure further supported the results from the remote sensing analyses (Table IV-2). Grazing probabilities correlated highest with the number of dung piles in reference plots (Spearman's $\rho = 0.58$) as well as with herbaceous biomass yield (Spearman's $\rho = -0.53$) with p-values always < 0.01. Other metrics were more weakly correlated with these field variables, but median TCW and DI_{steppe} were again best-performing (i.e., $\rho = -0.46$ and $\rho = 0.55$ with dung piles, respectively, and $\rho = 0.32$ and $\rho = 0.32$ with biomass yield, respectively). Standard deviation was 12.6 for the dung piles and 51.4 g/m^2 for the biomass yield. Correlations of top-performing metrics with dung piles were generally higher than with biomass. Comparing the variation of grazing metrics for field plots evaluated as 'heavily grazed', 'moderately grazed', or 'ungrazed' further confirmed the high performance of our grazing probability metric in separating these classes (Figure IV-4). Distribution of Tasseled Cap components reflected the expected patterns as well, specifically in regards to Tasseled Cap greenness, which was indeed higher on heavily grazed plots compared to moderately or ungrazed plots, particularly early in the season.

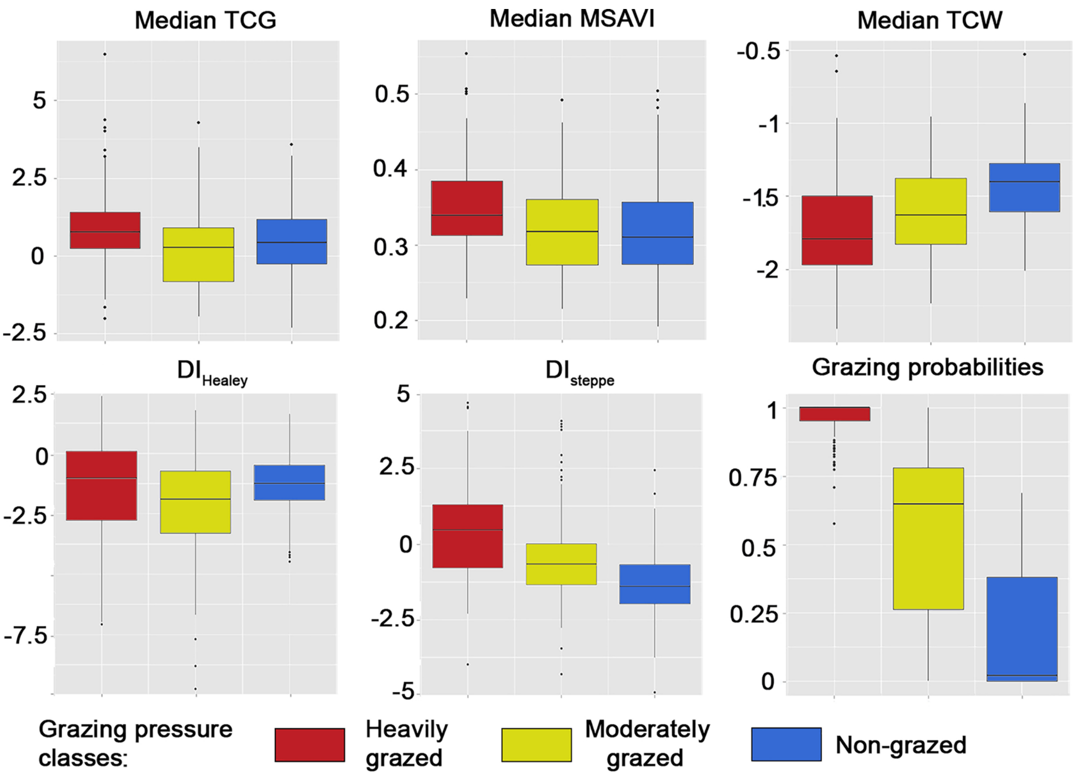

Figure IV-4: Variation in grazing metrics for three field-assessed grazing pressure classes. Only a selection of the most common metrics that were tested is shown here. Y-axes show the respective metric values (TCG = Tasseled Cap Greenness, MSAVI = Modified Soil-Adjusted Vegetation Index, TCW = Tasseled Cap Wetness, DI = Disturbance Index).

Our best-performing grazing metric (i.e., the class probability of the heavily grazed class) revealed distinct and highly plausible spatial patterns of grazing (Figure IV-5). We found two major types of grazing patterns: circular grazing footprints appeared predominantly around livestock concentration points (i.e., around livestock stations and settlements, Figure IV-5).

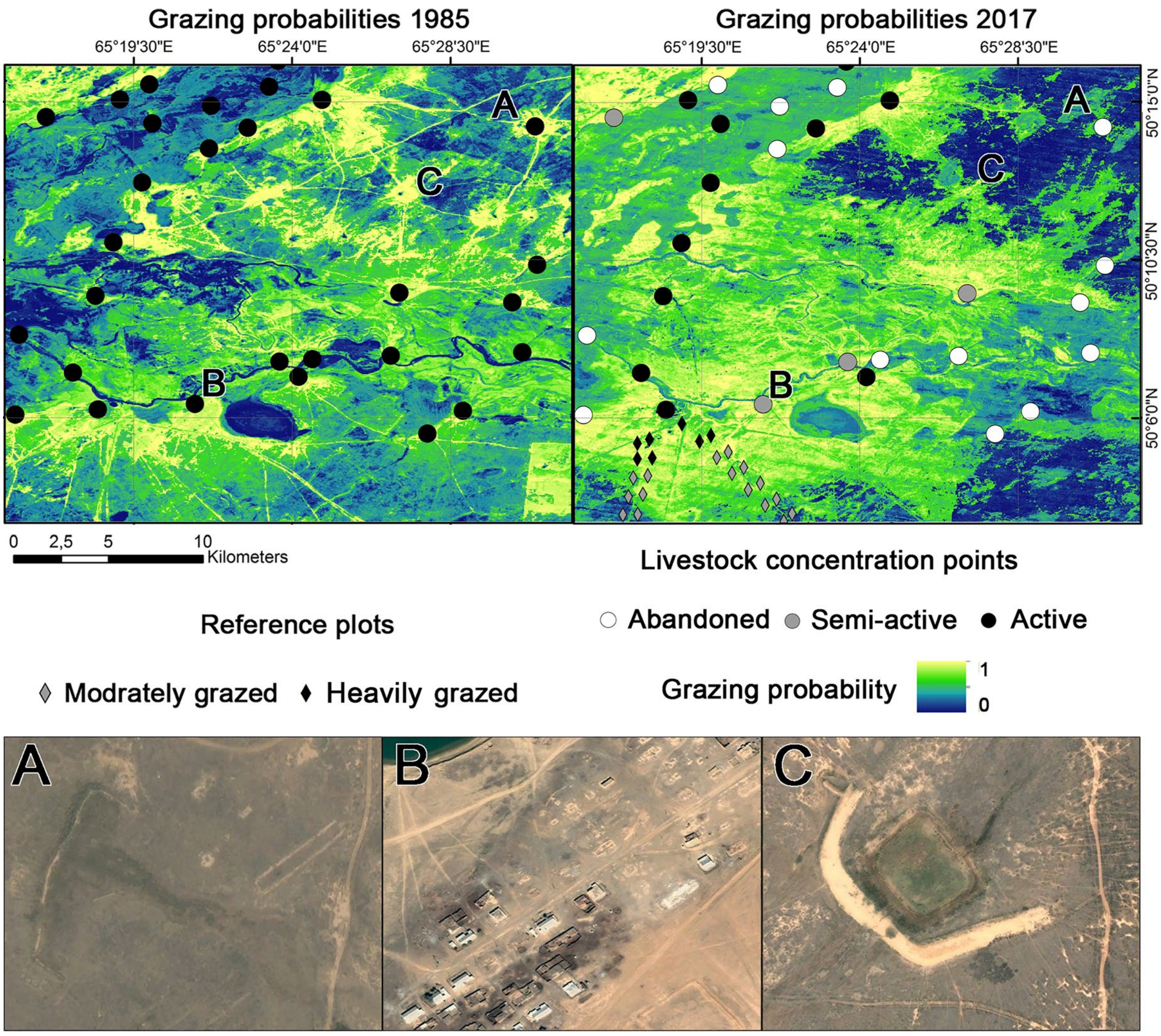

Figure IV-5: Grazing pressure as represented by the class membership probability of the class 'heavily grazed' (derived using a random forest model) in 1985 (upper-left) and 2017 (upper-right). Insets A-C: Examples of livestock concentration points in Google Earth. A: Abandoned winter livestock station with a watering point in 2006 (dam of watering point collapsed and not maintained). B: Active settlement with signs of abandonment in 2006. C: Active watering point (dam maintained) in 2006.

Assessing changes in heavily grazed areas over time highlighted a peak of 20.9 (±1) % (equaling 74,952 ± 3,514 km^2) of the study area as heavily grazed in 1988, which dropped to only 4.2 (±1.2) % (15,062 ± 4,267 km^2) by 2002, and then increased again slightly to 5.7 (±1.2) % (20,442 ± 4,196 km^2) by 2017 (Figure IV-6D). This temporal trend mirrored the trend in livestock numbers in our study region (Figure IV-6D). Analyzing how changes in grazing probability differed among abandoned, semi-active, or active livestock concentration points revealed marked temporal patterns (Figure IV-6A-C). First, grazing probabilities were generally similarly high for all types of livestock concentration points in the Soviet period, as the decline in livestock number and the partial or full abandonment of livestock stations started only after 1990. Second, differences in grazing pressure for different types of livestock concentration points were most pronounced for areas close to these points, as can be expected as the area over which livestock is distributed increases nonlinearly away from these points (Figure IV-6).

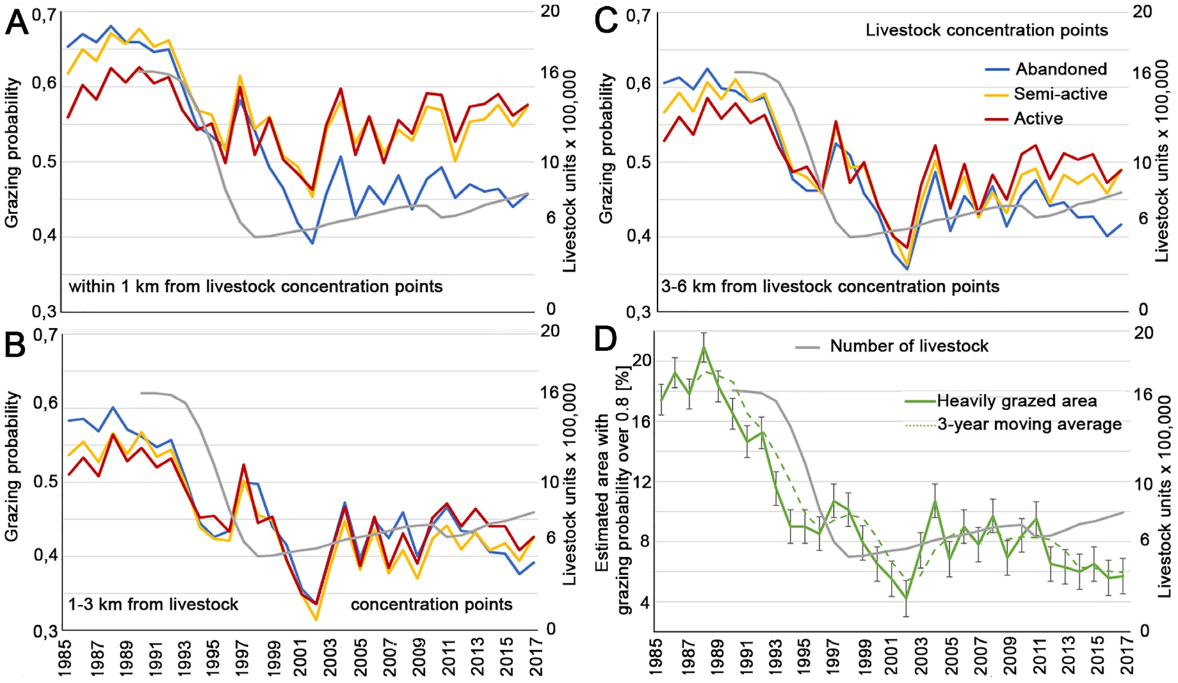

Figure IV-6: Change in average grazing probability within 1 km (A), 3 km (B), and 6 km (C) buffers around livestock concentration points from 1985 to 2017. Three groups of livestock concentration points are separated for each graph, according to usage intensity. Please note that all points of livestock concentration were likely still in use in the Soviet period, at least until 1990. Panel D shows the aggregated overgrazed areas (i.e., area estimates of grazing probability > 0.8) in relation to the total livestock number in the rayons covered by our study region for 1990 to 2017.

LandTrendr revealed clear spatial patterns in grazing pressure trends in our study area (Figure IV-7). About 45,000 km^2 (or 8.4 % of the study area) showed decreasing trends of grazing pressure (defined here as trends > 10 years, magnitude > 45 %, and grazing probability before the onset of change > 0.8). Across most of the study area, recovery duration was longer than 30 years (blue colors in Figure IV-7). Areas with shorter recovery trends were mainly located close to active livestock concentration points. Areas with widespread abandoned settlements had the strongest magnitude and long duration of recovery.

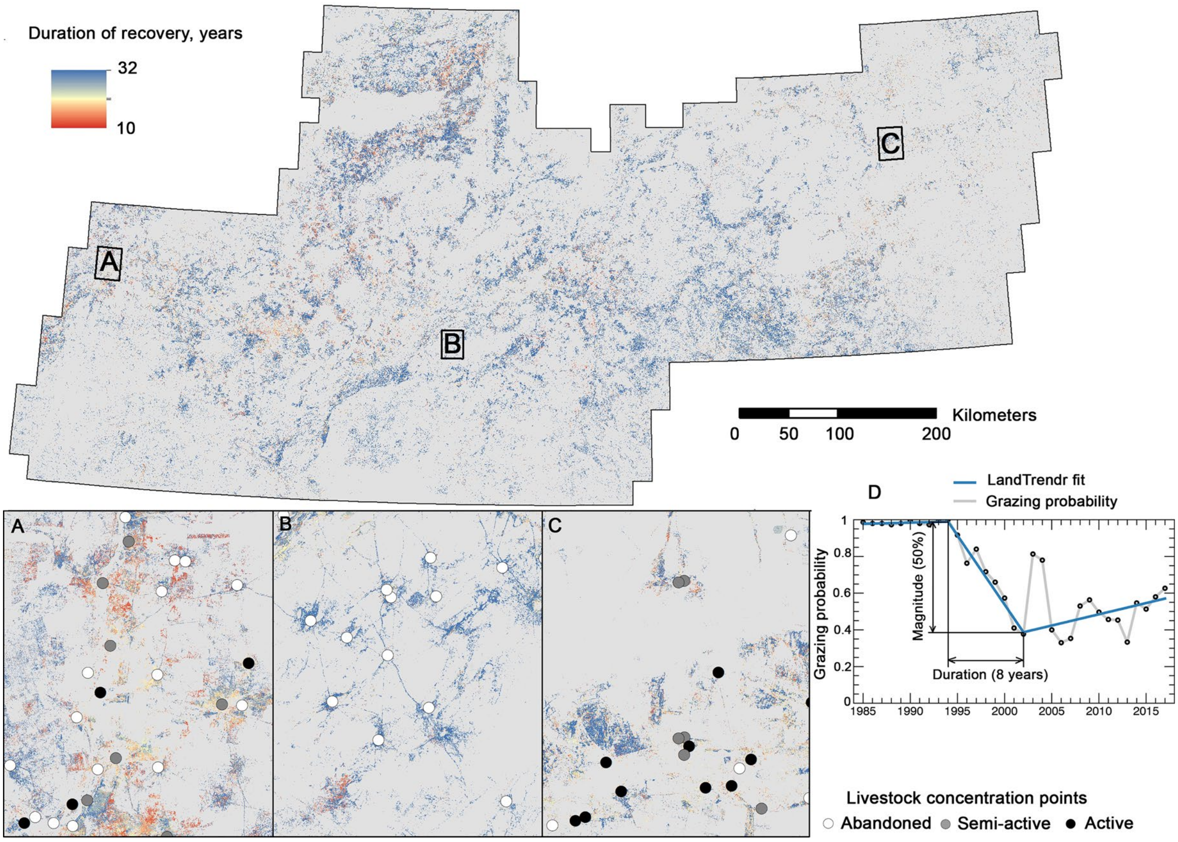

Figure IV-7: Recovery trends in the study region. Recovery trends are defined as LandTrendr segments >10 years, with a high change magnitude (> 45 %) and an initial grazing probability of at least 0.8. A-C: Three typical recovery patterns due to declining grazing pressure are shown in insets. D: Schematic explanation of key trend parameters of LandTrendr for one exemplary pixel showing 7-year declining trend in grazing pressure starting in 1994 and an 8-year recovery trend starting in 2001.

Recovery trends were stronger for livestock concentration points with the lowest use intensity (Figure IV-8), and recovery increased away from such points, in line with the findings outlined above. Areas of increasing grazing pressure (as defined in our analyses: trends > 10 years, magnitude > 45 %) were negligible. Even relaxing LandTrendr parameters to find shorter and more gradual trends of increasing grazing pressure (e.g., 5 years duration, 25 % magnitude) did not result in a substantial increase in areas flagged as experiencing rising grazing pressure.

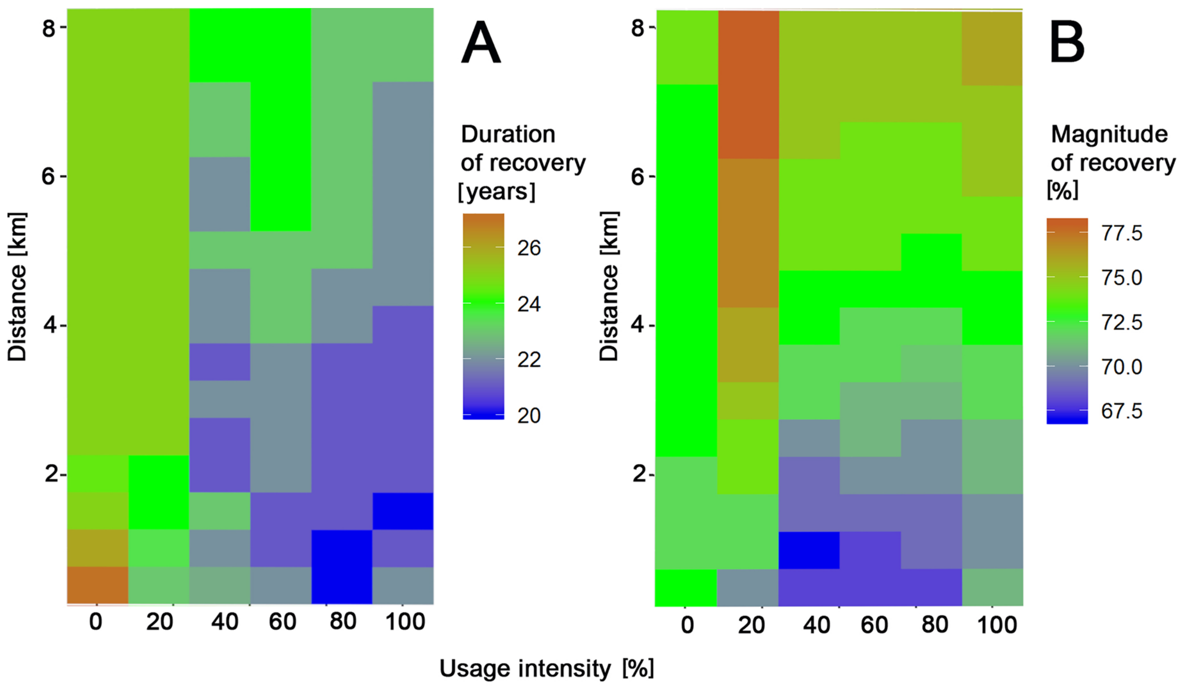

Figure IV-8: Two measures of vegetation recovery in response to changing grazing pressure (color gradient) for different levels of usage intensity of livestock concentration points (x-axis) and the distance away from these points (y-axis). A: Magnitude of a trend change relative to the initial grazing probability. B: duration of this trend.

4 Discussion

Grazing is globally widespread, but how the spatial footprint of grazing and grazing pressure varies in the world's grasslands remains largely elusive. This is problematic, because livestock grazing has far-reaching impacts on the biodiversity, ecological functioning, and ecosystem services of grasslands. Here, we present a new methodology that allows to reconstruct grazing pressure across large areas and back in time, based on the Landsat archives and contemporary field data on grazing pressure. We demonstrate the usefulness of this approach for a 360,000 km² region in the steppes of Kazakhstan, where grazing pressure dropped drastically after the breakdown of the Soviet Union.

Our three-step approach to first calculating spectral-temporal metrics, second using a classifier to derive grazing probabilities, and third to use trajectory analyses to map grazing trends based on classification probabilities yielded robust and highly plausible results and has a number of advantages. First, it allows to overcome limitations related to the scarcity and uneven density of Landsat imagery in the 1990s, which is common in many parts of the world (Kovalskyy and Roy, 2013) and particularly across Central Asia (Wulder et al., 2008). Second, it allowed to make full use of the Landsat archive and, in combination with field data on grazing, to identify a very reliable grazing pressure metric (Figure IV-4, Table IV-2). Importantly, the type of metrics capturing grazing pressure best might vary, depending on regional context, so this step can be beneficial to transfer our approach to other regions. Finally, the temporal segmentation allowed to separate long-term trends, in which we were interested here, from year-to-year variation in spectral values, which can be influenced strongly by climate variation as well (Archer, 2004).

We found our grazing probability metrics, derived by a random forest classifier from annual spectral-temporal metrics, to capture grazing pressure well. Using annual spectral-temporal metrics instead of individual images allowed for more homogenized and consistent time series, thus mitigating missing values due to data gaps or cloud contamination (Griffiths et al., 2013), as well as the impact of difference in observation dates. Testing a wide range of alternative spectral grazing metrics helped us to understand the value of individual metrics. For example, our DI_{steppe} was typically outperforming more generic spectral metrics (e.g., vegetation indices, NBR, original Tasseled Cap components), as DI_{steppe} was adjusted to the soil and vegetation conditions of our study region. This confirms the value of context-specific transformations (de Beurs et al., 2016; Liao et al., 2015), and suggests that our DI_{steppe} could be useful in other grassland areas with similar soil characteristics. Among the more generic metrics, Tasseled Cap components were best-performing in our study area, in line with earlier work (Karnieli et al., 2008). Importantly though, using all available metrics to derive a grazing class probability was far superior (e.g., 89 % overall accuracy vs. max. 78 %, when using single metrics). Our grazing probability metric correlated with a range of field-based grazing indicators, such as the number of dung piles and aboveground biomass, separated the three ground-validated grazing classes best, and yielded highly plausible patterns of grazing footprints in our study area. To the best of our knowledge, no studies exist that quantified grazing pressure in grassland ecosystems based on remote sensing at comparable spatial scale and resolution, and therefore we cannot compare our accuracy measure.

Comparing the aggregated area estimates identified as heavily grazed by our approach with independent data on livestock numbers further bolstered trust in our metric, as both time series matched well (Figure IV-6). Moreover, this comparison confirmed that the collapse of the livestock sector shortly after the breakdown of the Soviet Union (Kamp et al., 2011) translated into an immediate, strong, and widespread drop in grazing pressure across northern Kazakhstan. As expected (Kamp et al., 2011; Kamp et al. 2012, Röder et al., 2007), these declines were strongest in the immediate vicinity of the abandoned livestock concentration points and the effect waned away from these points and with declining levels of usage intensity (Figure IV-6). Smaller discrepancies between trends in satellite-based mapping of grazing pressure and livestock numbers can be explained by three factors. First, year-to-year variations in grazing pressure might partly be related to climate variations (as highlighted by the very good fit of the smoothed time series of high grazing pressure and the livestock numbers). For example, the small but noticeable change in grazing pressure from 2009 to 2011 we detected may actually be the result of a severe drought in 2010, which extended into 2011 and 2012 (rainfall diagram on Figure IV-1; Guo et al., 2018; Trenberth and Fasullo, 2012). It is important to highlight though, that climate variations over our study period were overall low and do not explain the strong trends in vegetation-related change that our metrics capture (de Beurs and Henebry, 2004). Second, livestock numbers do not provide information on the share of animals grazed vs. animals reared in feedlots, which might have changed recently (Kamp et al., 2016). Third, agricultural statistics in post-Soviet countries are sometimes biased or unreliable (Burkitbayeva and Oshakbayev, 2015; Kraemer et al., 2015).

The Landsat archive, with 30 m resolution, multi-spectral data available since 1984, allowed us to reconstruct the spatially heterogeneous changes in grazing pressure that characterize our study region, highlighting the value of these archives for retrospective analyses (Washington-Allen et al., 2004; Wulder et al., 2011). The maps visually resembled a network across the steppe landscape, with the nodes being livestock concentration points (livestock stations, watering points, settlements) and the linkages between these nodes as linear structures along which livestock typically moves (e.g., riversides and roads). Many nodes coincided with our mapped livestock concentration points, and those that did not were typically watering points in the steppe (i.e., wells, dams, and ponds; which were not mapped as livestock concentration points), as identified in high-resolution imagery in Google Earth (Figure IV-5). A similar pattern was observed around a watering point in rangelands in the US, using Landsat and AVIRIS images (Harris and Asner, 2003). Such grazing network patterns are not detectable using coarser resolution imagery (e.g., AVHRR), and while moderate-resolution sensors, such as MODIS, might capture parts of these patterns, these sensors do not reach back in time to the Soviet period. This highlights the outstanding value of the Landsat archive to understand land-use/cover histories. The results of our analyses, specifically the annual maps of the grazing pressure ‘network’ (Figure IV-5) can be a valuable dataset for many applications, including downscaling livestock statistics (Hankerson et al., 2019), calculating fine-scaled biomass use (Klaus et al., 2016), or assessing Human Appropriation of Net Primary Productivity (Gingrich et al., 2015).

While there is no viable alternative to the Landsat archive for retrospective, fine-scale analyses, this situation will likely improve due to advances in remote sensing technology. For example, the now operational Sentinel-2 mission greatly increases data availability. Furthermore, multi-sensor, data fusion and harmonization approaches, such as the Harmonized Landsat and Sentinel-2 (HLS) product, will increase the temporal resolution of fine-scale data substantially (Claverie et al., 2018), thus providing new opportunities for monitoring grazing pressure. Differences in phenology of grasslands could be then captured by algorithms such as BFAST (Verbesselt et al., 2010b, 2010a). Similarly, future hyperspectral missions (e.g., EnMap) raise hopes to better distinguish and identify subtle differences in grazing pressure (Leitão et al., 2015). Moreover, advances in computational capacities and cloud-based solutions are rapidly developing. For example, LandTrendr, the backbone of our analysis, has recently been implemented in Google Earth Engine (Kennedy et al., 2018).

Our results suggest a strong general recovery of standing biomass and vegetation in the steppes of Kazakhstan. Our LandTrendr analyses revealed remarkably detailed spatial patterns of recovery in response to changing grazing pressure. For instance, we found a higher magnitude of recovery farther away from livestock concentration points, suggesting these areas were abandoned earlier than the areas closer to the livestock concentration points. Similarly, our analyses revealed many areas of remote steppe that are recovering but were unknown to be heavily grazed prior to 1991 (e.g., around watering points). Likewise, we found many settlements where grazing pressure remained high during the 1990s and 2000s – in contrast to common belief. Our data also suggest livestock herders again use larger areas since 2010, due an increased hiring of communal shepherds, who can take flocks to more remote pastures (Robinson et al., 2017). As a final example, recovery trends were shorter or absent around more actively used livestock concentration points, suggesting that efforts in rebuilding the livestock sector focus on livestock stations and settlements that were never completely abandoned, rather than reactivating fully abandoned sites (Figure IV-1). We underline that we used heavily grazed areas as the baseline using field data that span from 2009 to 2016. Therefore, we can only map the recovery relative to this baseline.

Overall, this suggests that the steppes of Kazakhstan have shifted from predominantly high grazing pressure in Soviet time to a mosaic of heavily and lightly/ungrazed steppes in the post-Soviet era. The absence of recovery around actively used and the absence of increasing grazing pressure since 2013, despite a growth in livestock numbers, may point to a rise of feedlot-based animal husbandry. This is particularly important considering increased litter and biomass accumulation (Brinkert et al., 2016) due to the undergrazing across vast areas. The latter is one of the reasons for more and larger fires in the region since the Soviet era (Dara et al., 2019; Dubinin et al., 2011). In accordance with Hankerson et al. (2019), we suggest that the revival of the livestock sector on one hand, and the restoration of populations of wild grazers, such as Kulan (*Equus hemionus kulan*) (Zharbolova and Young, 2018) and Saiga antelope (*Saiga tatarica*) (Singh and Milner-Gulland, 2011) on the other can both help to restore important grazing-related ecosystem processes in the Kazakh steppes.

5 Conclusion and outlook

The spatial footprint of grazing, and how it changes, is largely unknown for most grassland regions globally. Our study, to the best of our knowledge the first to reconstruct fine-scale spatiotemporal grazing patterns for any steppe region in the world, highlights the outstanding value of the Landsat archives and image spectral-temporal metrics to do so. Using rich and diverse field data on grazing pressure for the parameterization and validation of our approach, we were able to show that our grazing metric outperformed a wide range of other spectral-temporal metrics, captured grazing pressure change over time very well, and was a robust indicator of changing grazing pressure in space. Our study furthermore demonstrated the ability of temporal segmentation (here: via LandTrendr) of class probabilities to capture long-term grazing effects in grasslands, mitigating the influence of short-term disturbances, such as fires and mowing that would hinder comparisons of snapshots in time.

Changes in grazed areas over time closely resembled known trends in livestock numbers after 1991 and highlighted that grazing pressure dropped drastically right after the breakdown of the Soviet Union due to the collapse of state farming system, rural outmigration, and loss of guaranteed sales market (Becker et al., 2005; Meyfroidt et al., 2016; Swinnen et al., 2017). Reconstructing the spatial footprint of grazing showed spatially heterogeneous pattern of grazing pressure changes, with declining grazing pressure over wide areas of the steppe, but also local concentration of grazing pressure around settlements – in line with field-based work (Kamp et al., 2012). This suggests biomass accumulation over wide areas of the steppe, with possible implications for fire regimes (Brinkert et al., 2016; Dara et al., 2019). Although Kazakhstan's livestock sector has recovered to some extent, recent increases in livestock numbers did not translate into major increases in grazed area, suggesting that the intensification of livestock systems, with feedlot-based livestock fed by crops, is playing an increasing role. Likewise, a current concentration of livestock in the hands of private owners who cannot afford herding on more remote pastures, a lack of shepherds due to rural outmigration, and lacking funding for restoring abandoned watering infrastructure can explain these patterns (Kamp et al., 2015; Kerven et al., 2016).

The approaches and maps developed in this study can guide decision-making and planning. For example, our maps could be used for an optimized redistribution of grazing pressure by the local decision-makers for an effective and sustainable revival of the livestock sector. Similarly, together with datasets of changes in cropland extent (Dara et al., 2018), our maps could be used for conservation planning projects, such as the reintroduction of wild ungulates, establishment of conservation areas, or corridor planning (Baumann et al., In review), all of which are official goals of the Kazakh government (Ministry of Agriculture of the Republic of Kazakhstan, 2018). More broadly, the methodology proposed here can be transferred to other grassland regions to monitor their current extent and intensity of use, and to reconstruct a historical grazing pressure.be transferred to other grassland regions to monitor their current extent and intensity of use, and to reconstruct a historical grazing pressure.

Acknowledgements

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Supplementary Material

Table SM IV-1: All grazing metrics based on (a) individual performance in single-metric random forest models with the 95% confidence interval, (b) the importance of metrics when using all metrics in one random forest model. NBR = Normalized Burn Ration, EVI = Enhanced Vegetation Index, MSAVI = Modified Soil-Adjusted Vegetation Index, TCW = Tasseled Cap Wetness, TCB = Tasseled Cap Brightness, TCG = Tasseled Cap Greenness, DI = Disturbance Index.

Metrics	*Overall accuracy [%]*	*95% Confidence Interval [%]*		*Feature importance*
NBR Mean	67	64	71	1.57
NBR Median	67	64	71	1.89
NBR p10	68	65	72	2.82
NBR p90	65	62	69	2.38
EVI Mean	69	65	72	1.78
EVI Median	68	64	72	2.52
EVI p10	68	64	72	3.31
EVI p90	69	65	72	1.06
MSAVI Mean	73	69	76	3.08
MSAVI Median	70	67	74	4.71
MSAVI p10	70	67	74	2.06
MSAVI p90	65	61	69	1.28
TCW Mean	75	72	78	3.60
TCW Median	76	73	80	7.13
TCW p10	75	72	79	6.49
TCW p90	69	66	73	2.16
TCB Mean	69	65	72	3.50
TCB Median	70	66	74	5.41
TCB p10	69	65	73	5.32
TCB p90	69	66	73	4.05
TCG Mean	71	67	74	4.20
TCG Median	72	68	75	3.33
TCG p10	62	58	66	2.76
TCG p90	73	70	77	1.98
DI Dara	78	75	81	15.60
DI deBeurs	73	70	76	2.55
DI Healey	72	68	75	3.47
Grazing probability*	89	87	92	N/A

** Based on a random forest classification model using all 27 metrics.*

Chapter V:
Synthesis

1 Summary

The overarching goal of this thesis was to gain a better understanding of land-use changes and their consequences in the steppes of Kazakhstan. The dissertation covered the years from 1985 to 2017, which has been an important period in the history of Kazakhstan that was marked by the transition from a state-driven to market economy. This transition resulted in a loss of guaranteed sales market and a drastic decrease in subsidies of agriculture with consequent widespread agricultural abandonment (Meyfroidt et al., 2016; Prishchepov et al., 2012a; Swinnen et al., 2017). Agricultural production in Kazakhstan dropped sharply as a results of the policy, market, and institutional changes after the collapse of the Soviet Union (Prishchepov et al., 2012a; Swinnen et al., 2017). This decrease of agricultural activity in areas that were previously utilized mainly for crop cultivation or livestock herding caused a dramatic intensification of fire regimes with far-reaching consequences (Dubinin et al., 2011). Moreover, the land resources that fell out of agricultural production provide a large opportunity for steppe restoration and a revival of large ungulates that previously inhabited the Kazakh steppes (Appendix A). Although local authorities are seeking to restore wildlife population in the area as well as for reviving the livestock sector (Meyfroidt et al., 2016; Ministry of Agriculture of the Republic of Kazakhstan, 2018), spatially explicit information on extent and timing of land-use changes as well as on changes in fire regimes have been limited.

Mapping cropland abandonment and recultivation as well as changes in grazing pressure in the face of the data scarcity in the region (Kovalskyy and Roy, 2013) is a non-trivial task and required development of novel methodologies. These methodologies largely relied on a combination of existing technologies (i.e., spectral-temporal metrics, class probabilities, and LandTrendr) that proved their robustness in a number of different tasks, such as mapping forest cover change (e.g., Griffiths et al., 2013; Pflugmacher et al., 2014; Senf et al., 2015). In this thesis multi-temporal spectral-temporal metrics (Frantz, 2017; Griffiths et al., 2013) have been shown to allow for partially overcoming data scarcity in mapping cropland and fire extent, as well as grazing pressure. Random forest helped to derive cropping and grazing probability accurately, as well as to allocate burned areas. Temporal segmentation using LandTrendr (Cohen et al., 2010; Kennedy et al., 2010) was helpful for detecting dates of cropland abandonment and a subsequent recultivation (if it took place) and for mapping trends of grassland recovery after intensive grazing. The resulting land-use and burned area change maps, analysed using numerous spatial and statistical tests, were instrumental in understanding the processes that happened in the Kazakh steppes after the dissolution of the Soviet Union.

By applying these methods, the two key research questions asked in this thesis could be answered:

Research Question I: How to map changes in cropland and burned area extent as well as in grazing pressure in a steppe ecosystem given scarce data?

Chapter II focused on mapping the timing of cropland abandonment and recultivation. A novel approach was developed to overcome gaps in the Landsat archive in the 1990s (Kovalskyy and Roy, 2013; Loveland and Dwyer, 2012). Three-year spectral-statistical metrics (Frantz, 2017; Griffiths et al., 2013) allowed creating annual time series from all available Landsat imagery despite missing values in some years. These time series were then used in a binary random forest classifier (Breiman, 2001) with screen-digitized reference points (Cohen et al., 2010) of croplands vs. non-croplands to create annual maps of cropland probabilities. The resulting time series of cropland probabilities were fitted in LandTrendr (Kennedy et al., 2010). Finally, we used a change-detection algorithm to detect breakpoints with a three-year moving window. This resulted in two maps of cropland extent change: a map of cropland abandonment timing from 1988 to 2013 and a map of recultivation timing from 1991 to 2013. The aggregated map yielded high overall accuracy (89 %), while user's and producer's accuracies for individual years of cropland conversions were generally lower and varied widely. These variations were explained by impact of low image availability, especially in the late 1990s – early 2000s. Some of the abandoned fields that were omitted in the 1990s were detected later, when image availability increased.

In Chapter III, we produced three burned area maps. One represents the late Soviet period (1989-1991), one the period of lowest agricultural extent (1999-2001), and the last captures the recent period after the partial recovery of agriculture (2014-2016). These maps were created by classifying Landsat-derived spectral-statistical metrics from each three-year period with a random forest classifier. Reference data for burned vs. unburned areas were collected using monthly Landsat NBRT time series (Holden et al., 2005) and the MODIS burned area product in Google Earth Engine (Gorelick et al., 2017). Burned area maps demonstrated high overall accuracies of 99, 94, and 96 percent for the maps centred in 1990, 2000, and 2015 respectively.

Chapter IV focused on mapping changes in grazing pressure from 1985 to 2017. In contrast to previous two Chapters, it was possible to derive annual spectral-statistical metrics, due to slightly better data availability in the pasture-dominated south of the study area. Extensive reference data of grazing pressure with a number of biophysical parameters, such as the number of dung piles and the biomass yield (Brinkert et al., 2016), allowed for testing a number of different grazing metrics. Tasselled Cap-based components performed better than other single metrics in two tests based on a random forest classifier, and showed a better separability of grazing classes using boxplots. They also correlated better with the biophysical parameters. However, grazing probabilities, i.e., probability of a pixel belonging to the class "heavily grazed" in a binary random forest classification using all single grazing metrics performed best. The overall accuracy of this classification was 90 % and Spearman's ρ with the number of dung piles was 0.54. Annual grazing probability maps produced using this model exhibited clear visual patterns, resembling a "neural network" with "neurons" being livestock concentration points, such as livestock stations, settlements, wells, and ponds; and "axons" being roads, and riversides. Finally, a grassland recovery map was produced using LandTrendr with a recovery lasting longer than 10 years, and a magnitude of these trends > 45 percent. This map showed visual patterns similar to the grazing pressure maps from 1980s.

Research Question II: What was the environmental impact of post-Soviet land-use change in the steppes of Kazakhstan?

Maps of cropland abandonment and recultivation timing developed in in Chapter I revealed important spatiotemporal patterns of cropland extent change in northern Kazakhstan after the breakdown of the Soviet Union. 40 percent of croplands have been abandoned in the period; however, 20 percent of this area have been brought back into production by 2013. In line with previous research (Kraemer et al., 2015), most of the abandonment happened in the 1990s, peaking in 1995. However, the fine temporal details of the map allowed for detecting a second smaller wave of abandonment in 2007 to 2009. The map of recultivation timing showed that the major recultivation wave started in the beginning of the 2000s, peaked in 2005, and decreased afterwards. Most areas abandoned in the first wave were located on less fertile areas, while the second wave took place mostly on marginal lands, most likely due to the limitations in infrastructure (Kraemer et al., 2015; Meyfroidt et al., 2016). However, the croplands that were abandoned more recently were more likely to be recultivated. This finding, in line with Kraemer et al. (2015), suggests a further reorganization of crop production in Kazakhstan towards the most fertile areas. Finally, 16.3 ± 3.5 Mt. of soil organic carbon sequestration from 1992 to 2012 was estimated using the annual abandonment and recultivation maps. This is 80 percent more than if merely assuming 1990 as a year of all cropland abandonment, or 47 percent less than if assuming this date in 2010.

Burned area maps from Chapter III revealed a sevenfold increase in burned area and an eightfold increase in the number of fire scars in 2000 as compared to 1990. Although total burned area slightly decreased in 2015, it remained substantially larger than it was in 1990. Most of the fire regime intensification was associated with changes in land use or land-use practices. On the one hand, use of agricultural burnings boomed in the area in 2000, although their number decreased afterwards. On the other hand, significant intensification of fire regimes also happened on the abandoned croplands and on the previously grazed areas, probably due to an increase in dry litter accumulated in the steppe in the absence of grazing (Brinkert et al., 2016; Dubinin et al., 2011). This has likely markedly affected air quality (McCarty et al., 2017; Stohl et al., 2007).

Chapter IV demonstrated a sixfold decrease in grazed areas starting in the early 1990s. This decrease reflected both declined number of pastures and a contraction of the remaining pastures, i.e. grazing became more concentrated. Most of the grassland recovery started from the very beginning of the study period, however, some shorter trends occurred around livestock concentration points that have still been in use. Considering the increase in livestock numbers in the area since 2000, this observation suggests that Kazakhstan is not redistributing grazing pressure by reanimating abandoned livestock stations. This probably negatively impacts the steppe ecosystem due to both undergrazing and overgrazing (Alimaev et al., 2008; Brinkert et al., 2016; Kamp et al., 2016).

2 Main conclusions and implications

2.1 Main conclusions

Together the results of the three core chapters answered the two questions stated in this dissertation and contributed to reaching the overarching goal. The main insights that are following from the Chapters II-IV foster understanding of processes that followed the dissolution of the Soviet Union in the steppe belt of Kazakhstan.

Chapters II, III, and IV emphasized the value of the Landsat imagery for mapping changes in land use and burned areas in steppe regions. All three core chapters underlined the usefulness of high spatial resolution of Landsat. Abandonment and recultivation of agricultural fields would not be possible to detect using coarse resolution imagery e.g., AVHRR (Propastin et al., 2008). Similarly, it is difficult to detect agricultural burning in the area with MODIS imagery (Hall et al., 2016; McCarty et al., 2017). A “neural network” pattern of grazing pressure also requires finer resolution than MODIS, as the “axons” are comprised of thin lines along the roads and riversides that served for taking livestock to and from pastures.

Continuity of the Landsat archive since 1980s (Wulder et al., 2008) played a key role in mapping historical land use and fire regimes in the area. No other satellite mission had a combination of spatial resolution appropriate for mapping fine details of land-use change and burned areas, and a temporal depth covering the late post-Soviet era. Despite the gaps in observations in the 1990s and in the early 2000s (Kovalskyy and Roy, 2013), it was possible to map cropland abandonment and grazing pressure with annual time step from the Soviet period until recent times. Chapter II is the only study that provides a fine-scale burned area map for the period of 1989-1991 in Kazakhstan.

Overlaying the cropland and cropland abandonment maps with the maps of grazing pressure did not result in a substantial overlap in the land uses, and therefore the combination of the maps from Chapter II and Chapter IV provide a holistic and consistent land-use change assessment of the part of the study areas that overlaps. This area is smaller than the study areas presented in each of the core chapters, however it covers the most important area for grain production in Kazakhstan and also includes the area with the highest concentration of abandoned croplands, a part of the largest single Chernozem strip with stable croplands, and a large area where grazing pressure decreased (Figure V-1). Minor traces of grazing were found mostly on edges of croplands that are close to settlements or pastures, possibly because farmers let their livestock graze on crop fields after harvest or before sowing. Almost no expansion of grazing to abandoned croplands occurred. The main trend of cropland and grazing reorganization was towards concentration of croplands on the most fertile soils and of pastures around the active settlements, leaving large areas unutilized. This can be explained by the majority of livestock kept by private owners for semi-subsistence (B. R. Hankerson et al., 2019; Robinson and Milner-Gulland, 2003).

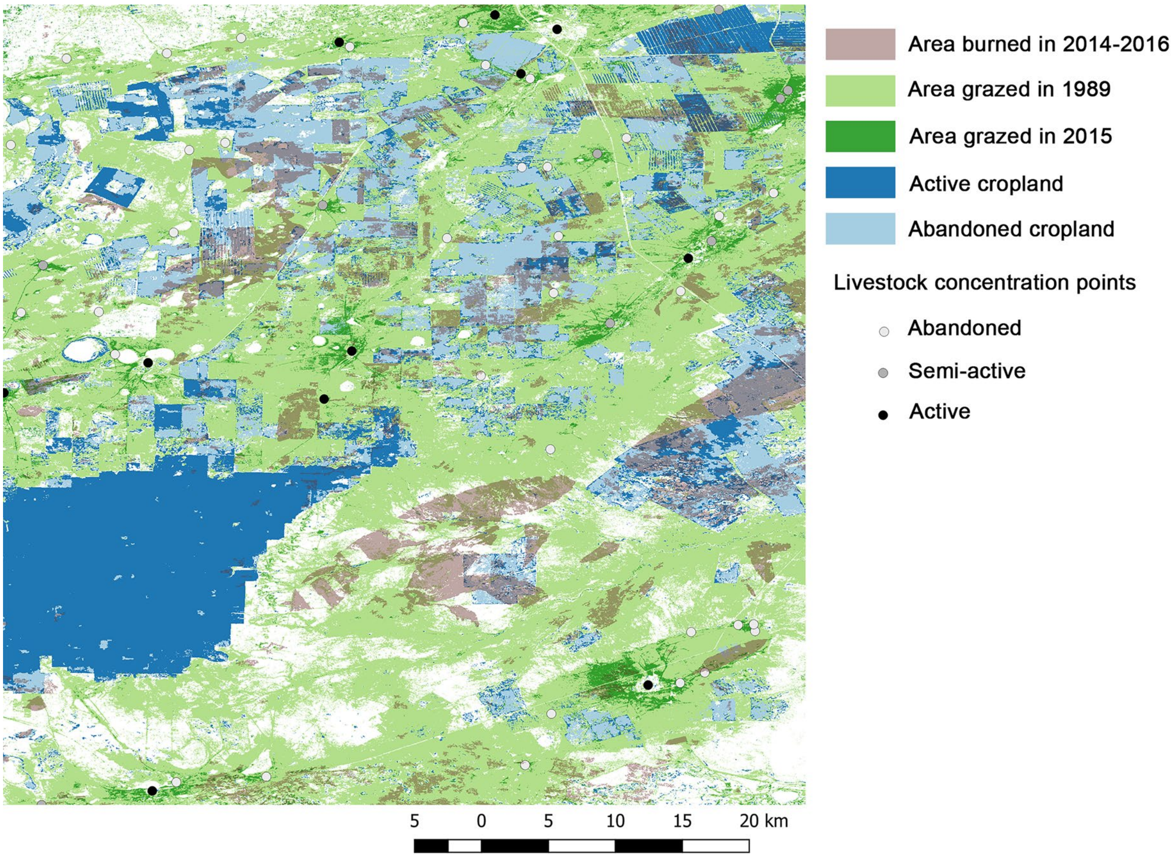

Figure V-1: A map of land-use change from 1989 to 2015 with areas burned in 2014-2016. Burned areas have 50% opacity, so that land-use of burned area could be seen.

Temporal patterns of cropland extent change and grazing pressure change were similar after the breakdown of the Soviet Union. Both crop and livestock production experienced a dramatic drop in the mid-1990s, and gradually recovered since the early 2000s. Agricultural abandonment has been driven by the loss of a guaranteed sales market, drastic decrease in agricultural subsidies, and emigration of qualified labour force, largely to Russia and Germany (Becker et al., 2005; Meyfroidt et al., 2016; Swinnen et al., 2017). This resulted in a downward spiral for job opportunities and led to further emigration from the rural areas of northern Kazakhstan to the larger cities or to abroad (An and Becker, 2013). A decade after the start of the first abandonment wave, the second wave of cropland abandonment followed. Attempts of reviving agricultural production had a certain level of success, but were limited by lack of qualified labour, decay of infrastructure (Robinson and Milner-Gulland, 2003; Meyfroidt et al., 2016), and high levels of corruption on all levels (Oka, 2015; O'Neill, 2014; Uberti, 2018). The annual cropland and grazing maps developed here allowed to uncover the effects of these complex patterns related to the transition process on post-Soviet land-use change in space and time.

The post-Soviet changes in land-use and land-use practices had large consequences for Kazakh steppe ecosystem functioning. First, cropland abandonment resulted in carbon sequestration in the absence of soil disturbance (Sala et al., 1996; Wertebach et al., 2017). Annual maps of cropland abandonment and recultivation allowed estimating SOC significantly more precisely. Second, post-Soviet changes in land use and land-use practices negatively affected fire regimes in northern Kazakhstan. In the Soviet agricultural system, the wheat stubble remained on the fields after harvest and were used as fodder for livestock. In the absence of livestock, the farmers regularly burned the stubble (McCarty et al., 2017), which resulted in a drastic increase in air pollution. The traces of agricultural burning in Kazakhstan have been found as far as in Alaska (Stohl et al., 2007). Furthermore, the abandonment of cropland and grazing resulted in accumulation of dry biomass in the steppe, which serves as a fuel for larger and more severe wildfires (Brinkert et al., 2016; Dubinin et al., 2011). Fires in the study region took place disproportionally more on the abandoned croplands and pastures (Figure V-1 and Figure V-2). Another conclusion that could be made by inspecting maps of burned area and grazing pressure is that fires rarely happened on grazed areas (Figure V-2). This is in line with previous research on pyric herbivory, i.e., on spatiotemporal interaction of fire and grazing (Fuhlendorf et al., 2009). Therefore, more spatially distributed grazing might reduce fire hazard and fire severity in the Eurasian steppes (Brinkert et al., 2016; Dubinin et al., 2011). The last insight provided by the pyric herbivory map is that in spite of a rare overlap of fires and grazing, fires frequently bordered grazed areas. This observation may point to human-induced causes of fire in the region. Finally, a major consequence of agricultural abandonment in the region is a massive amount of newly available areas that may be used, e.g., for nature conservation or restoration purposes (Appendix A). However, grassland restoration often requires an adequate grazing and fire treatment (Fuhlendorf and Engle, 2004; Gerla et al., 2012).

2.2 Implications

The spatially explicit results of this dissertation, the insights they provide, as well as the developed methodology may find application in a wide variety of tasks. The Kazakh government may potentially use the maps of land-use change for planning their land-use policies, fire management, as well as for implementing restoration programs. The methods for mapping land-use change developed in Chapter II and Chapter IV may be applied for mapping similar processes in other semi-arid grassland regions of the world.

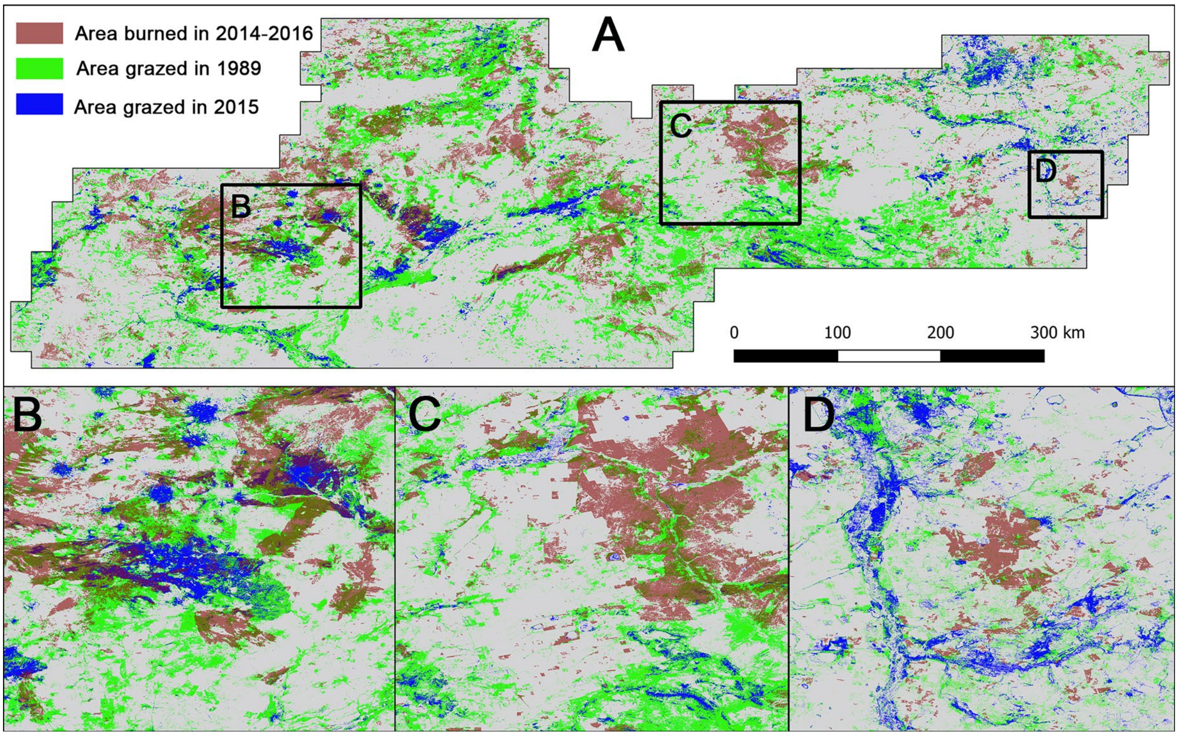

Figure V-2: Mapping pyric herbivory in northern Kazakhstan in 2015. (A) Area burned in 2014-2016 overlaid with the maps of high grazing pressure (grazing probability > 0.65) in 1989 and 2015. Burned areas have 50% opacity, so that it could be seen whether the area has been grazed. (B-D) The inlets showing typical pyric herbivory (grazing-fire) interactions.

The Strategic Plan of the Ministry of Agriculture of the Republic of Kazakhstan for 2017-2021 (Ministry of Agriculture of the Republic of Kazakhstan, 2018), which is an official agenda for implementation of goals of the Kazakh government, includes several directions that could potentially use the results of this dissertation. One such strategic goal is to improve the use efficiency of arable lands. According to the program, the Ministry of Agriculture is planning to diversify crop types, but also to increase crop production. The map of cropland abandonment timing from the Chapter II, in combination with maps of infrastructure and agricultural suitability, could be instrumental in an efficient and sustainable allocation of croplands after assessing the potential of these areas for steppe restoration. Existing spatial and statistically disaggregated datasets are highly unreliable (Burkitbayeva and Oshakbayev, 2015; Kraemer et al., 2015). For instance, the strategic plan states there are 4.55 million ha of abandoned agricultural land in the entirety Kazakhstan (Ministry of Agriculture of the Republic of Kazakhstan, 2018), while Chapter II shows 1.8 million ha abandoned only in a small study region, and Kraemer et al. (2015) shows 1.7 million in an even smaller region. Furthermore, it is important to consider that the croplands that have been abandoned longer ago tend to have higher conservation value, as it takes time for natural steppe vegetation to recover (Cramer et al., 2008; Gerla et al., 2012). It is also important to consider potential connectivity of protected areas when allocating agricultural land (Appendix A).

Another goal of the Kazakh government according to the Strategic Plan is to increase meat and milk production in Kazakhstan (B. R. Hankerson et al., 2019; Ministry of Agriculture of the Republic of Kazakhstan, 2018). The government aims to achieve higher livestock production through more efficient use of pastures, including improved availability of watering points and through increasing fodder production (among other means). Increasing fodder production could be facilitated by the map that captures the timing of cropland abandonment. Higher pasture use efficiency could be achieved by re-allocating existing pastures or reanimating abandoned ones. The map of grazing pressure change from Chapter IV could be an important tool in this regard. Releasing grazing pressure from the overgrazed areas would be beneficial for aboveground biomass available in these areas (Hölzel et al., 2002). In case a dataset of the livestock watering points is available, the grazing pressure map would be helpful for balancing grazing pressure between these watering points. Relocating grazing pressure from heavily grazed areas to underutilized pastures would reduce excessive dry biomass on the latter.

Dry biomass reduction through increased livestock grazing on the underutilized pastures could result in the reduction of potential fuel for wildfires (Brinkert et al., 2016; Dubinin et al., 2011). According to the Strategic Plan of the Kazakh government, steppe fires *have a detrimental effect on the condition of the animal world and on the whole of biological diversity, and cause significant damage to agriculture.* Taking into account large consequences of fires in the region (Archibald et al., 2013; Stohl et al., 2007), it is important to reduce fire regimes intensity in Northern Kazakhstan. A combination of the grazing pressure maps from Chapter IV with the cropland abandonment map from Chapter II, and the recent burned area map from Chapter III may be instrumental for developing fire prevention strategies. Prescribed grazing could reduce fire hazard on the undergrazed areas (Brinkert et al., 2016; Fuhlendorf et al., 2009; Fuhlendorf and Engle, 2004). Moreover, moderate grazing can be beneficial for restoration of abandoned croplands, as this might improve species richness (Cramer et al., 2008).

Conservation and restoration of flora and fauna have a high priority in the Strategic Plan as well. A successful program of reintroduction of Kulans (*Equus hemionus kulan*) implemented by the Association of Biodiversity of Kazakhstan takes place in Altyn Emel national park in central Kazakhstan (Zharbolova and Young, 2018). Restoration of saiga antelope population in steppe regions of Kazakhstan is also an aim of the government. A prerequisite for this ambitious goal is allocation of suitable habitat for the ungulates. An example of research that maps rewilding indicators and potential steppe habitat connectivity is provided in Appendix A. The study uses Landsat imagery to map cropland abandonment and recultivation in northern Kazakhstan and a dataset of abandoned and active livestock concentration points (the same as was used in Chapters III and IV) as a proxy to grazing pressure change. The research found that post-Soviet agricultural abandonment opened the door for rewilding in the steppes of northern Kazakhstan. Considering the large unused areas in the region, there should be no conflict between potentially restored populations of wild ungulates and potentially increased and redistributed livestock. The study provided plausible maps of rewilding indicators and connectivity. Nevertheless, using annual maps of cropland abandonment instead of three steps in time would allow for mapping a degree of steppe restoration and for a better separation of permanently abandoned croplands from short-term fallow fields. Using remote sensing-based grazing pressure maps instead of livestock concentration points would result in substantially more accurate estimates of the grazing footprint by eliminating the assumption of grazing distance around these points. Moreover, spatially explicit data on livestock watering points do not exist.

Finally, the methodology developed in the three core chapters is scalable and may be applied for the entire country. For instance, apart from aforementioned inconsistencies in the National Land Registry regarding estimation of an abandoned land, the Strategic Plan underlines insufficiency of GIS data in Kazakhstan available to the authorities as well as to the public. Improving quality and quantity of content of the Automated Information System of the National Land Cadastre is a high priority task of the Ministry of Information and Communication of the Republic of Kazakhstan in a framework of the “Digital Kazakhstan” program (Ministry of Information and Communication of the Republic of Kazakhstan, 2017). Methods from the Chapter II and IV may be used for mapping a current extent of croplands and pastures within larger administrative units. Furthermore, the methodology may be used for other grassland regions, especially in the countries of the former Soviet Union that are hampered by similar paucity of both remote sensing data as well as fine-scale agricultural statistics.

3 Outlook

This dissertation advanced understanding of land-use changes after the breakdown of the Soviet Union in northern Kazakhstan and their impact on ecosystem functioning. We developed a novel methodology for mapping cropland abandonment and recultivation, as well as changing grazing pressure using Landsat imagery, and we used this method to map land-use changes and burned areas over a large study region. With the advent of new datasets and tools that are constantly being developed and released, new opportunities for land system science are emerging. Although, these are out of scope of the dissertation, it is important to provide an insight of a potential future research in light of the current work.

Landsat imagery was used in all three core chapters for mapping land use change and burned areas. Having an appropriate spatial resolution, Landsat was the optimal satellite data available for the study period reaching back to the late Soviet era. A drawback for creating a continuous time series were observation gaps in the Landsat archive in the 1990s (Kovalskyy and Roy, 2013; Wulder et al., 2008), as time series density is crucially important for yielding a high accuracy in land-use change mapping (Hansen and Loveland, 2012; Roy et al., 2006). With the launch of the Landsat 7 in 1999 and the Landsat 8 in 2013, the revisit period was significantly reduced, and now a new Landsat observation is available every eight days (Wulder et al., 2016). This will be improved even further with the launch of the Landsat 9, which is expected in 2020 (Wulder et al., 2019). Virtual constellations of surface reflectance provide an excellent opportunity to combine satellite data from similar sensors in one dataset. The Harmonized Landsat and Sentinel-2 (HLS) is a perfect example of a continuous data cube that provides analysis-ready data with a revisit period of approximately 3.2 days at 55° latitude (Claverie et al., 2018). These recent advancements in earth observation will allow for more precise and temporally detailed mapping of land use processes.

Having dense time series would allow us to consider phenological differences, further improving the methods of cropland and grazing pressure extent change (Rapinel et al., 2019). This would enable using trend and breakpoint detection algorithms, such as the Breaks for Additive Seasonal and Trend (BFAST, (Verbesselt et al., 2010b, 2010a), or Time Series Segmentation and Residual Trend analysis (TSS-RESTREND, Burrell et al., 2017). Fusion of data from different sensors, such as MODIS and Landsat, may improve accuracy of burned area mapping (Boschetti et al., 2015), though MODIS imagery is not available for the Soviet period.

Another potential way for future improvement of the methodology developed in this dissertation is to increase the accuracy of the classification results. For instance, more advanced machine learning algorithms that are emerging, such as deep learning could be used (Reichstein et al., 2019; Zhang et al., 2019, 2016). This branch of machine learning is developing fast and has some promising examples of application in remote sensing, however it still has some uncertainties and limitations that are yet to be resolved (Ball et al., 2017; Reichstein et al., 2019). For example, substantially higher amount of training data is required for deep learning models, and the results are often lacking interpretability (Reichstein et al., 2019; Zhang et al., 2016). Furthermore, algorithms that are more complex require more computational power, while denser time series mean higher data volumes and require thus more storage capacity.

Cloud computing provides an opportunity to overcome limitations of computational power. Large IT companies such as Google and Amazon turned their data centres into scalable and elastic computational power pools equipped with a stack of technologies for distributed computing and big data processing (e.g., Map Reduce, Colossus, and BigTable at Google) known as *Public Clouds* that are "renting out" resources on demand (Armbrust et al., 2010; Dean and Ghemawat, 2004). One cloud geospatial solution based on the Google stack of technologies is Google Earth Engine (GEE; Gorelick et al., 2017), which is gaining popularity among remote sensing specialists (Shelestov et al., 2017). GEE is a powerful platform that allows for global scale mapping in a short time and provides an impressive number of tools for image processing, machine learning, and mapping. However, the tools are restricted to those provided by GEE's library, and thus their modification is not possible, potentially limiting their application. Although open source analogues to Google stack technologies, such as Apache Hadoop exist (Glushkova et al., 2019), building a cloud service similar to GEE would require setting up an expensive datacentre, which is cost prohibitive, e.g., for a public institution. GEE was used for several tasks in Chapter III and Chapter IV, and with the development of GEE functions the whole process of remote sensing analysis from the core chapters of this dissertation will be possible to reproduce in the cloud. This will enable the methods presented here to be applied to larger areas, or even to global temperate grasslands, provided a high quality and quantity of reference data.

With an increasing redistribution of food production and consumption, the importance of studying telecouplings, or distal connections between land systems, becomes crucial (Friis et al., 2016; E. F. Lambin and Meyfroidt, 2011; Meyfroidt et al., 2014). Beef trade between Russia and Brazil, mentioned in the Introduction to this dissertation, causes deforestation, forest degradation and greenhouse gases emission in South America (Henders et al., 2015; Machovina et al., 2015; Schierhorn et al., 2016). Before the dissolution of the Soviet Union, the demand for beef there was mostly satisfied domestically from cattle production in Soviet Russia, Kazakhstan, Ukraine, and Belarus. With the drop of beef demand in Russia, the livestock numbers in the region plummeted (Introduction, Chapter IV, and Schierhorn et al., 2016, 2013). Reviving the livestock sector in the Eurasian steppes might result in replacing imported beef from South America in the region by domestically produced meat. Furthermore, this could potentially increase the well-being of local rural population and decrease steppe fire hazard (Chapters III, Chapter IV, and Dubinin et al., 2011). Considering the large potential of Kazakhstan in livestock production (Chapter IV, Eisfelder et al., 2014; Hankerson et al., 2019), and construction of a new transportation system connecting the region with China (Dadabaev, 2018), the Eurasian beef could also partially substitute Brazil as a beef supplier in China and Iran, who are close neighbours of Kazakhstan and large importers of Brazilian beef (Figure V-3). This colossal task would require tremendous work, international collaboration, and thorough research in many spheres of scientific knowledge, and this dissertation may potentially be helpful in contributing to future research in this direction.

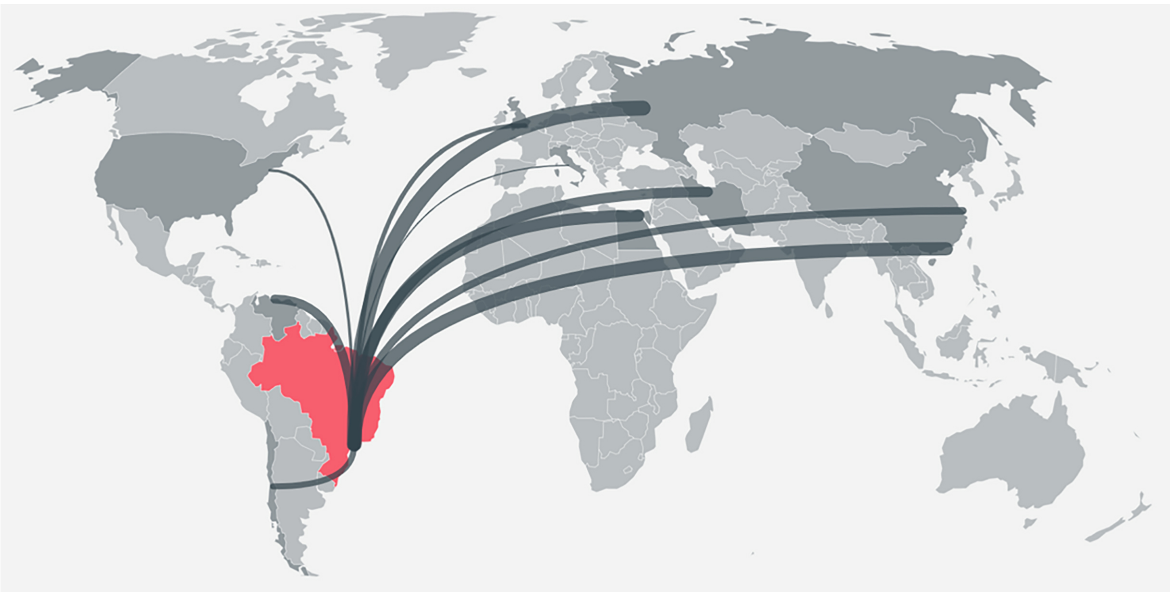

Figure V-3: A map of Brazilian beef export from www.trase.earth (Stockholm Environment Institute and Global Canopy). Russia, China, and Iran are Kazakhstan’s closest neighbours and are among the main consumers of the Brazilian beef.

The Kazakh steppe has undergone substantial land-use changes over the last century. The time of heavy agricultural use of the area was followed by massive land abandonment. The

Kazakh government's ambitious goals of sustainably reviving livestock numbers while restoring a part of the native steppe with its native wild ungulates is challenging and needs to be supported with solid baseline data. In this regard, this dissertation could facilitate decision-making processes by the local authorities. Moreover this dissertation fosters understanding of the historical land use in the region and suggests possible ways forward towards more sustainable futures. Ultimately, this dissertation contributes to the current state-of-the-art in Landsat-based time series analyses and thereby advances the field of remote sensing.

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Appendix A:
Declining human pressure and opportunities for rewilding in the steppes of Eurasia

(In review)

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Diversity and Distributions

Abstract

The world's temperate grasslands harbor exceptional biodiversity, are major carbon storages, and provide important ecosystem services. These ecosystems have also been under immense land-use pressure for centuries, leading to their widespread conversion to cropland and pastures. Protecting and restoring temperate grasslands are therefore conservation priorities. Much of Eurasia's temperate grasslands (hereafter: steppes) are found in the former Soviet Union, where the collapse of communism triggered substantial cropland abandonment, declines in livestock, and rural outmigration. This suggests considerable potential for steppe restoration, but the spatial patterns of declining human pressure remain elusive. Our overarching goal was to develop and map rewilding indicators for restoring large, connected steppe complexes. Focusing on a 38 million ha study region in northern Kazakhstan, we used multi-seasonal Landsat imagery to map cropland changes from 1990 to 2015, and digitized >2,000 settlements and >1,300 livestock stations from Soviet topographic maps and assessed their current status using high-resolution imagery. This showed massively declining human influence: about 6 million ha of cropland were abandoned (29% of all cropland), 14% of all settlements were fully and 81% partly abandoned, and 76% of livestock stations were completely dismantled. Combining these datasets into a steppe rewilding index identified where human pressure declined strongly since 1990, including major decreases within protected areas, resulting in an increase in the connectivity of steppe habitat. We conclude that this massively declining human pressure on Eurasia's steppes provides unique opportunities for steppe restoration, including of populations of wild grazers. Yet this window of opportunity may soon close, as the recultivation of abandoned cropland and resettlement of steppes are gaining momentum. Our rewilding index and maps can help to devise strategies for designing large, connected networks of protected areas in the steppe.

1 Introduction

Temperate grasslands are among the Earth's largest biomes. Rich in biodiversity, they also provide important ecosystem services such as carbon storage (Dixon et al. 2014). Many temperate grasslands are located on the most productive soils of the world and have therefore been widely converted to cropland, whereas less productive areas are commonly used as pastures (Wright & Wimberly 2013). As a result, natural grasslands are now scarce in the temperate zone. In North America, only small and isolated natural prairie patches remain amid a matrix of cropland (Zilverberg et al. 2018). In the Europe, not a single larger complex of pristine grassland habitat remains that still exhibits interactions between large herbivores, fire and vegetation (Wesche et al. 2016). As a result, many grassland species have been declining and are of conservation concern. Restoring temperate grasslands across larger areas is therefore a conservation priority (Fuhlendorf et al. 2018).

Recent socioeconomic trends may provide opportunities for achieving this goal. Given structural change and intensification in agriculture, marginal land in grassland regions is abandoned (Mottet et al. 2006; Estel et al. 2015) and secondary grasslands developing on these lands may connect previously isolated patches. This, turn, may allow to restore some of the currently missing trophic dynamics and disturbance regimes that are characteristic for grasslands. Such a rewilding, for the purpose of this paper defined as the active or passive a restoration of ecosystem functionality, including disturbance regimes, connectivity, and trophic interactions, would benefit biodiversity (Navarro & Pereira 2012; Corlett 2016) while providing co-benefits in terms of ecosystem services and resilience (Ceaușu et al. 2015). Yet, locating candidate areas for steppe rewilding remains a challenge, in part because rewilding research has often focuses on forests (Jepson 2016) and adequate tools are therefore missing. Furthermore, while the restoration potential of temperate grasslands has repeatedly been assessed, existing work has typically focused on small regions or individual sites within agricultural landscapes (Fuhlendorf et al. 2009). We are not aware of any rewilding assessment for grasslands across the broad scales needed to establish connected and self-regulating grassland complexes.

The Eurasian Steppe is particularly interesting in this context. This region, stretching from Eastern Europe to the Altai mountains, is situated nearly entirely in the former Soviet Union and contains the vast majority of Old-World steppe {Wesche, 2016 #5135}s. Remnant populations of large grazers, such as saiga antelopes (*Saiga tatarica*) or Kulan

(Equus hemionus kulan), still roam these steppes or have recently been reintroduced (Robinson & Milner-Gulland 2003; Kock et al. 2018). The region provides critical stop-over habitat for Eurasia's migratory birds, and hosts sizable populations of many species that are of high conservation concern in Western Europe (Kamp et al. 2016; Rounsevell et al. 2018).

Across the Eurasian Steppe, the extent and intensity of agriculture have decreased substantially after the collapse of the Soviet Union in 1991 (Meyfroidt et al. 2016; Schierhorn et al. 2016). Historically, nomadic pastoralism was the main land use in these steppes, yet vast areas were converted to cropland during the Soviet "Virgin Lands Campaign" from 1954 to 1963 (Durgin 1962). After 1991, as a result of institutional change, diminishing support for agriculture, and large-scale human outmigration (Schierhorn et al. 2013; Lesiv et al. 2018), at least 48 million ha of cropland were abandoned across Russia and Kazakhstan alone (Swinnen et al. 2017). In Kazakhstan, grazing livestock numbers decreased by as much as 70% (Lioubimtseva & Henebry 2012; Schierhorn et al. 2016), while remaining livestock were increasingly concentrated around larger settlements (Kamp et al. 2015; Hankerson et al. 2019). As a result, many areas previously used for agriculture are now undergoing secondary succession (Brinkert et al. 2015; de Beurs et al. 2015; Wesche et al. 2016). An assessment of the broad-scale spatial patterns of declining human influence in these steppes that would allow the formulate rewilding visions, however, is lacking.

The opening of the Landsat image archives, containing images back to the early 1980s, can help to close this knowledge gap (Pereira & Navarra 2015; Zhu et al. 2019). Novel image-compositing methods now allow for the consistent mapping of land change across very large areas (Potapov et al. 2015; Dara et al. 2018), including of cropland abandonment in the former Soviet Union (Yin et al. 2018). Similarly, new high-resolution satellite imagery, such as those available in Google Earth, can help to proxies of changes in human pressure on steppes. Analyzing these datasets synergistically should allow to pinpoint candidate areas for steppe rewilding, and to understand where it is feasible to expand and link existing protected areas into large, functioning steppe reserve networks.

Our overarching goal was to develop and map rewilding indicators using satellite imagery and historical maps, and to use these indicators to identify areas for broad-scale steppe restoration. Focusing on northern Kazakhstan and the period 1990-2015, we asked:

1. What were the patterns of post-Soviet changes in cropland area, livestock density, and human population density across the steppe?
2. Where are steppe areas that are undergoing passive rewilding, and which spatial determinants characterize these areas?
3. How has declining human influence affected the connectivity among protected areas in the region?

2 Methods

2.1 Study area

Our study region comprises three provinces in north-central Kazakhstan (Kostanay, Akmola and North Kazakhstan oblasts), covering 380,000 km² (Figure A-1). The region extends across three ecoregions, namely forest steppe, steppe, and semi-desert (Olson et al. 2001), with a rainfall gradient from 400 mm in the north to 200 mm in the south. The climate is continental with average temperatures of 22°C in July and -18°C in February (Afonin et al. 2008). The study area contains most of Kazakhstan's rain-fed cropland, primarily used to produce wheat (Meng et al. 2000; Kraemer et al. 2015). Crop-growing conditions are not ideal due to frequent droughts (Lioubimtseva & Henebry 2012) and short growing seasons. Yields are thus comparatively low, with wheat yields averaging around 1 ton/ha (KAZSTAT 2011). Across the entire Kazakh steppe region, protected areas have expanded onto former croplands and pastures, increasing from 0.76 million ha in 1991 to 3.87 million ha in 2015.

2.2 Mapping changes in cropland extent

To map changes in the extent of cropland, we generated Landsat image composites for the years ca. 1990 (i.e. the end of the Soviet era), ca. 2000 (first decade of the transition period, and the period where land-use intensity declined strongest), and ca. 2015 (current situation, after a partial revival of the agricultural sector). Image composites are gap- and cloud-free mosaics based on Landsat images (Griffiths et al. 2014; Griffiths et al. 2018). For each of the three time steps, we calculated three composites centered on spring (Julian day 121), summer (180) and fall (260) to capture phenology differences that are important for mapping cropland-grassland dynamics (Baumann et al. 2011). We also calculated a set of spectro-temporal metrics for which we considered all available cloud-free observations for each year.

We gathered training data through on-screen digitization of high-resolution images in Google Earth, visual examination of the Landsat composites, and land-use information collected in the field (see Dara et al. 2018 for details). We then classified our Landsat image composites using random forests , a non-parametric machine-learning technique (Breiman 2001). Finally, we applied a minimum mapping unit of 10 Landsat pixels (equal to 0.9 ha) and validated the resulting land-cover map using 100 randomly sampled points per class, following best-practice protocols (Olofsson et al. 2014). Our land-cover change map had an overall accuracy of 86.3% (see Supporting Information).

2.3 Mapping changes in human population density and livestock distribution

We assumed that the densities of human population and free-ranging livestock were directly related to human pressure on steppes. We therefore assessed changes in the conditions of settlements and livestock-related infrastructure from the Soviet period until today. Livestock stations in the study area are outposts where livestock are concentrated in summer ('Letovkas') or winter ('Zimovkas'). These stations usually consist of up to three houses or tents ('yurts') for shepherd accommodation, stables and corrals. To assess changes in settlement and livestock station density, we digitized both for circa 1984 (representing infrastructure in the Soviet period) and circa 2012 (representing the current situation). For the Soviet period, we manually digitized settlements and livestock stations across the study region (n = 6,482) from georeferenced, declassified Soviet military topographic maps scaled 1:200,000. For the current situation, we used publicly available**,** high-resolution satellite images (2.5 m resolution or higher) in Google Earth and Bing Maps, to determine the level of intactness of settlements and livestock stations (10% intact, 20% intact, etc.). For further information on the digitization process see Supporting Information.

2.4 Developing and mapping a steppe rewilding index

Using our maps of cropland extent, grazing stations and settlements, we mapped changes in the level of human influence (Carver et al. 2012) from 1990 to 2015. We generated three layers with a common spatial resolution (300m; 10x10 pixels in our land-cover map) that mapped (a) the share of cropland per grid cell, (b) the distance to settlements, and (c) the distance to livestock stations. We scaled the values from 0 to 1 such that higher values represented higher human influence (e.g., areas near active livestock stations and settlements). Next, we combined these three layers into a 'human influence index', comparing two alternatives: (a) the product of the three layers (assuming overall pressure is the combined impact of these pressures), and (b) the average of the three layers (i.e., assuming additivity of pressures; see Supplementary Material). Last, we calculated changes in our human influence indices from 1990 to 2015, which resulted in a 'steppe rewilding index', which captures the extent to which areas are undergoing passive rewilding ranging from 0 (low) to 1 (high).

2.5 Changes in landscape connectivity due to rewilding

To assess how changes in human influence impacted connectivity among steppe patches, we assessed landscape connectivity using circuit theory (McRae & Kavanagh 2012). Circuit theory describes the movement of individuals through a landscape by considering all possible pathways between gridcells. Each pathway can be interpreted as a current. Gridcells that are part of many pathways thus have a higher current density compared to gridcells that are part of fewer pathways. The cumulative current density map of all pathways can be interpreted as overall landscape connectivity (Koen et al. 2014).

To assess overall landscape connectivity, we randomly selected 50 nodes within an initial buffer around our study region with a width of 50% of the study region extent. For each node pair we mapped current density, using the human influence index as a resistance surface. We then increased the buffer size in increments of 5% of the study region extent, created a new set of random nodes, re-calculated the current density map, and compared this map to the previous map using Pearson's correlation coefficient. The optimal buffer size was reached when the resulting map had $r>0.98$ compared to the map from the previous buffer (Koen et al. 2014; Leonard et al. 2017). Once we had current density maps for 1990 and 2015, we calculated the difference between the two maps (for details on the connectivity analyses, see Supporting Information).

2.6 Rewilding effects on protected area connectivity

To evaluate how rewilding affected protected areas, and to assess whether new protected areas were place in regions were passive rewilding was prevalent, we compared our rewilding index to the network of protected areas. We obtained the boundaries of all protected areas in the study region from the Committee of Forestry and Wildlife, Ministry of Agriculture of Kazakhstan. In July 2018, there were 44 officially registered protected areas in Kazakhstan, covering about 24.9 million ha (i.e. 9% of the country area). Protected areas in Kazakhstan are categorized as follows: Strict State Nature Reserves

("Zapovedniks", IUCN category Ia) are wilderness areas with no permitted use except research. National parks (IUCN category II) are specially protected areas of historical, cultural or natural value used for scientific research and recreation. "Reservats" (Rezervaty, IUCN category Ib or II) are areas for sustainable use of local resources with a focus on nature conservation. Finally, local reserves ("zakazniks", IUCN category IV), are smaller protected areas with a zoological, botanical or geological focus where land use is restricted but allowed.

3 Results

3.1 Cropland change

Our satellite-based assessment showed widespread cropland abandonment (Figure A-1). From the estimated ~203,000 km^2 under crops in 1990, 59,164 km^2 had been abandoned by 2015 (i.e., a decrease of 29.2%). The abandonment rate was much higher during 1990-2000 (56,766 km^2 abandoned, 28.0% of all cropland in 1990) compared to 2000-2015 (14,899 km^2 abandoned, 10.2% of all cropland in 2000, Figure A-2). After 2000, we also found substantial recultivation, with 9,685 km^2 (17.1%) of the area abandoned during 1990-2000 being re-cultivated by 2015 (Figure A-2).

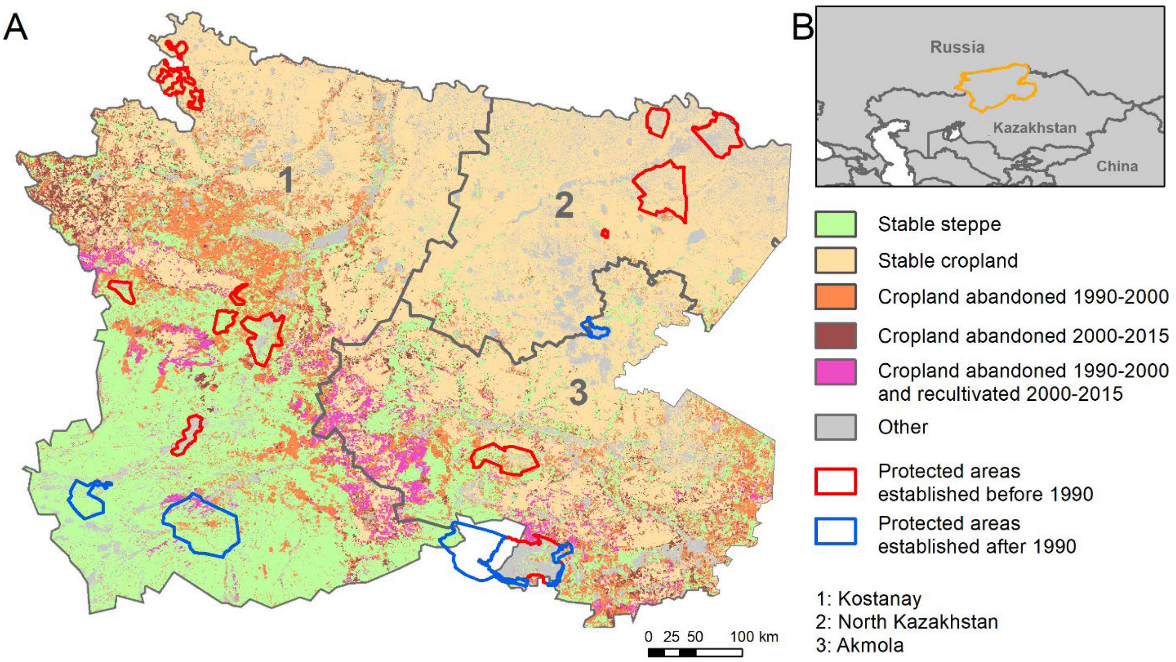

Figure A-1: (A) Cropland dynamics in the study area, mapped from Landsat images. (B) Location of our study area in northcentral Kazakhstan.

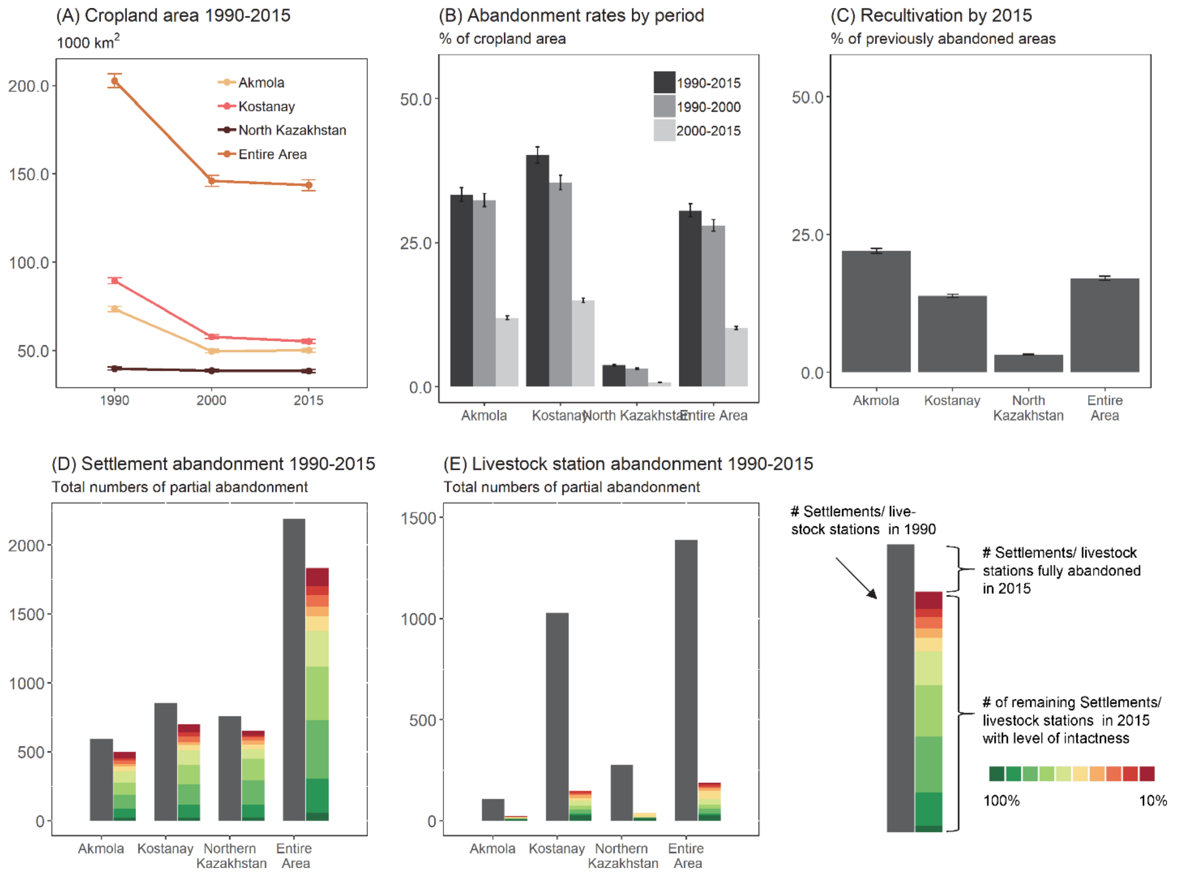

Figure A-2: (A) Extent of cropland in the study area between 1990 and 2015. (B) Cropland abandonment per province and for the entire study area. (C) Recultivation of cropland in 2000-2015 of areas abandoned in 1990-2000. Error bars in A-C represent 95% confidence intervals in area estimates. (D-E) Settlement and livestock station abandonment 1990-2015.

The extent of abandoned cropland varied substantially across the three provinces, with high rates in Kostanay (45.0% abandoned, equalling 40,391 km^2) and Akmola (40.4%, 29,733 km^2), but a much lower rate in North Kazakhstan (3.8%, 1,530 km^2 Figure A-2). From 1990 to 2000, cropland area contracted the most in Kostanay (31,736 km^2 or 35.4%), followed by Akmola (23,786 km^2 or 32.4%) and North Kazakhstan (1,242 km^2 or 3.1%), with much lower rates during 2000-2015 (Akmola 12.0% or 5,946 km^2, Kostanay 14.9% or 8,654 km^2, North Kazakhstan 0.7% or 288 km^2) (Figure A-2). Recultivation of cropland (5,245 km^2 in total, 22.0% of all cropland abandoned until 2000) was highest in Akmola (5,245 km^2) and Kostanay (4,400 km^2), but much lower in North Kazakhstan (40 km^2).

The number of settlements also decreased substantially between 1990 and 2015 (Figure A-2). Across the entire study area, 14% of all settlements were completely abandoned, 81% were partly abandoned (i.e., with at least 10% of all buildings demolished), and only 5% of all settlements remained intact or increased in size (Figure A-2). Regarding livestock stations, abandonment rates were even higher, with ca. 83% of all summer stations (Letovkas) and 90% of all winter stations (Zimovkas) completely abandoned (i.e., no signs of use in ca. 2012), and an additional 16% of all summer stations and 7% of all winter stations at least partially dismantled. Only 1% of all summer and 3% of all winter stations used during Soviet times were still in use in 2015. We did not find any new livestock stations, nor stations that were larger now than they had been in Soviet times (Figure A-2).

3.2 Declining human pressure on steppes

The post-Soviet trends of contraction in cropland, outmigration of rural population, and decline in livestock stations during the 1990s and 2000s resulted in massively decreased human influence on Kazakhstan's steppes (Figure A-3). Combining our three spatial indicators (cropland change, settlement change, livestock station change) into the human influence indices showed substantial variation in human pressure across our landscape. Human influence during Soviet times was lowest in southern Kostanay, where livestock grazing was the dominant land use. In contrast, across northern Kostanay. as well as in North Kazakhstan and Akmola. cropland was more abundant, generally resulting in higher human influence. After 1991, human influence generally decreased across the region. The decrease was strongest in Kostanay, whereas North Kazakhstan did not show a noticeable decline in human influence.

Assessing steppe rewilding across the network of existing protected areas in our study region highlighted that, on average, the level of human pressure inside protected areas decreased substantially between 1990 and 2015. Expectedly, in nearly all protected areas, human influence values decreased, regardless of protection level (i.e., IUCN categories I-VI, Figure A-3). Before 1990, only protected areas of IUCN categories I and IV existed in the region, and category I protected areas showed lower human influence values than category IV areas, except for Tounsor and Sarykopa Zakazniks. Since 1990, four new protected areas were established (one each of categories I and II, and two of category VI), which were placed in regions of relatively low and decreasing human influence (Figure A-3).

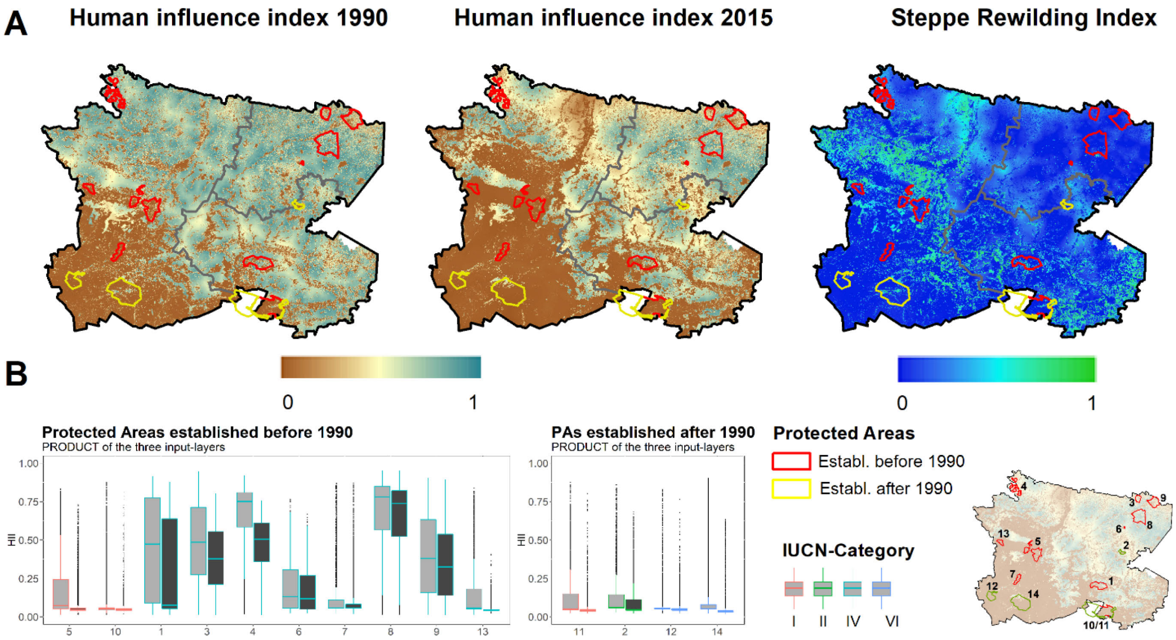

Figure A-3: (A) Human influence index 1990 and 2015 as well as the steppe rewilding index for our study area (we here show human influence calculated as is the product of the three input layers). (B) Human influence index within the protected area network. Boxplot shades represent years (1990: light grey; 2015: dark grey). A list with full names of the protected areas is provided in the Supplementary Material.

3.3 Changes in connectivity on the landscape scale

The changes in human pressure also resulted in marked changes in landscape connectivity. Most of the areas where landscape connectivity increased were in Kostanay, whereas in North Kazakhstan and Akmola such areas were not widespread (Figure A-4). Relative to protected areas, however, decreasing human influence resulted in increased connectivity between older protected areas in central and southern Kostanay, and southern Akmola. Likewise, new protected areas (i.e., protected areas established after 1990) in these two regions were generally in areas of higher connectivity. Landscape connectivity also increased between protected areas in central Kostanay (i.e., between Naurzum Zapovednik, Tounsor and Sarykopa Zakazniks, Figure A-4). Finally, some areas we found to have a high landscape connectivity were facing increasing human pressure through cropland recultivation, particularly on the border between Kostanay and Akmola (Figure A-4B).

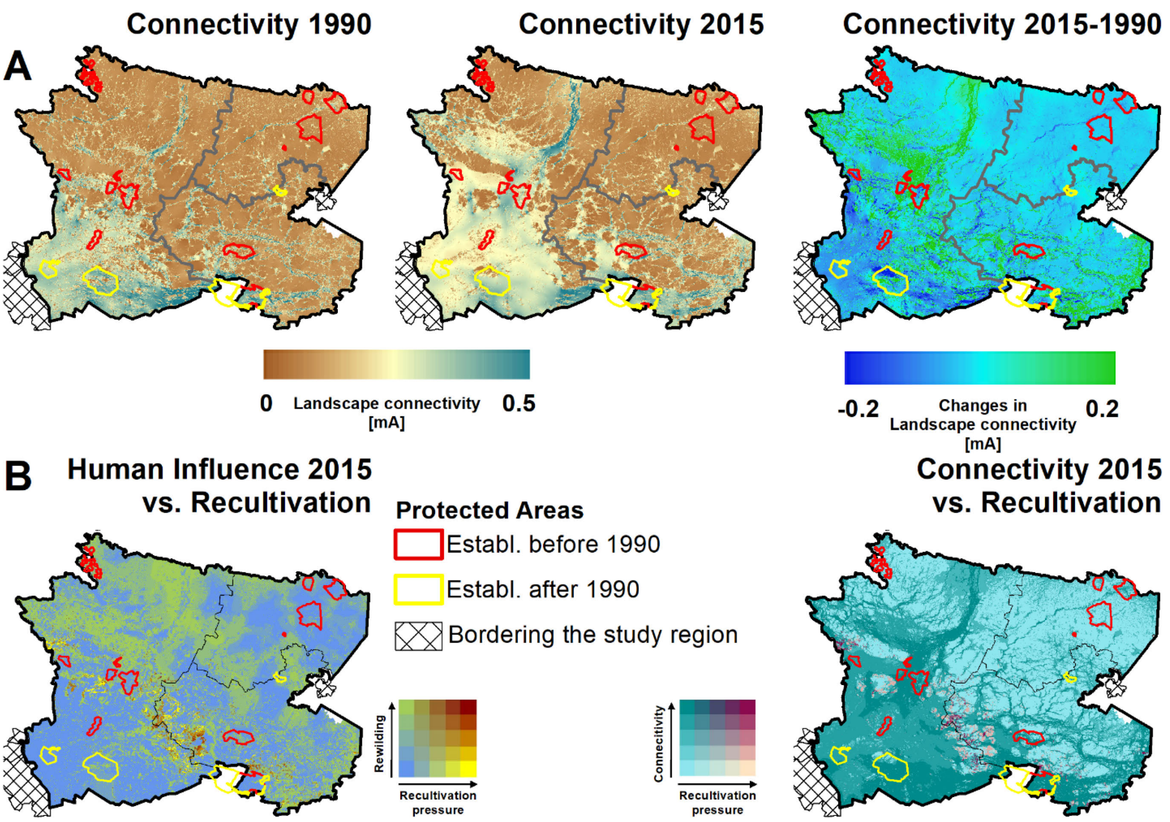

Figure A-4: (A) Changes in landscape connectivity between 1990 and 2015. (B) Human influence index (left) and connectivity (right) in relation to recultivation pressure. Recultivation pressure refers to areas which were abandoned 1990-2000 and then recultivated in 2000-2015.

4 Discussion

The world's temperate grasslands have historically been transformed profoundly due to land-use change. Restoring large, ecologically-functioning grassland complexes, that foster trophic dynamics, natural disturbances, and the interactions between fire and native grazers that have shaped these grasslands for millenia, is a bold conservation vision (Fuhlendorf et al. 2019). Post-Soviet changes in land use may provide opportunities for rewilding some of the largest and last remaining stretches of temperate grasslands in Eurasia: the Eurasian steppes. However, adequate spatial data for designing strategies to do so have so far been lacking.

Focusing on a 38 million ha region of the Eurasian steppe in Kazakhstan, we designed and mapped a new steppe rewilding index, based on changes in cropland extent, grazing pressure and human population density. Our study provides three main, novel insights. First, our analyses highlight a massive decline in human pressure following the collapse of the Soviet Union in 1991, with more than 52,000 km² of cropland abandoned, more than 97% of livestock grazing stations disappearing or drastically downsizing, and more than

90% of all settlements partly or fully dismantled. These declines in human influence suggests substantial potential for restoration and conservation. Second, our analyses pinpoint areas currently undergoing passive rewilding trends and highlight that these areas have the potential to link existing protected areas. Protected area networks in our study are sparse and isolated, and recent trends can help to establish a protected area network that benefit a wider array of species, such as large ungulates, and natural processes, such as grazing-vegetation-fire interactions, than currently. Finally, while our study highlights major conservation potential, the window of opportunity for implementing such broad-scale protected area networks may soon close as recultivation of abandoned cropland is gaining momentum.

Cropland abandonment and outmigration of rural populations happened across the former Soviet Union, but here we show that human pressure declined particularly strongly in the steppes of Kazakhstan. Across the former Soviet Union, cropland abandonment was high in European Russia, Belarus, and Ukraine (Prishchepov et al. 2012; Schierhorn et al. 2013; Smaliychuk et al. 2016), with abandonment rates of over 40%, and the cropland abandonment rates we document for northern Kazakhstan were similarly high (up to 45% in Kostanay). Importantly though, ours is the first study that quantifies the additional, massive decline in grazing pressure – for any steppe region in the former Soviet Union – with an area footprint many times larger than that of cropland abandonment (Figure A-3). In the case of northcentral Kazakhstan, the main drivers of these trends were large-scale human outmigration (Meyfroidt et al. 2016), the transition from state to market-driven economies (Rozelle & Swinnen 2004), which made crop production unprofitable, as well as the collapse of state-owned farms. While agricultural sectors have rebounded to some extent after 2000, many of the land-use changes that have happened since 1991 are likely to persist (e.g., because Soviet era agriculture expanded onto marginal areas, or because infrastructure has been dismantled since 1991). Northern Kazakhstan should therefore be a priority region for (active or passive) rewilding with the goal to restore steppes.

Identifying areas where passive rewilding takes place, and measuring progress towards more functional, self-regulating, and complex ecosystems, have become central research themes (Torres et al. 2018). Our steppe rewilding index captures key dimensions of declining human impact, and maps the spatial extent and patterns of areas undergoing spontaneous rewilding (Navarro & Pereira 2012; Svenning et al. 2016). Importantly, our index is widely applicable, given the increasing availability of high-resolution satellite imagery, both current (e.g., Sentinel-II, Planet, imagery accessible in Google Earth or

Bing) and historical (e.g., Landsat archives, air photos, Corona imagery). Likewise, the historical maps we used are available across the entire Eurasian Steppe, and similar maps are available elsewhere. Our work thus also underlines the value of making historical maps available, here used to identify Soviet-era livestock stations, in order to understand historical human pressure.

There is evidence that passive rewilding in Eurasia has major ecological impacts, which could potentially restore important ecological functions. Most obvious in our study was that declining human influence increased landscape connectivity. Moreover, cropland abandonment has increased soil carbon pools (Schierhorn et al. 2013; Meyfroidt et al. 2016; Wertebach et al. 2017). Likewise, large wild grazer populations have rebounded from high poaching rates in the 1990s to some extent (Bragina et al. 2015), and several trophic rewilding initiatives are now underway to bring back native grazers to areas where they have disappeared (Kock et al. 2018). Similarly, fire activity has increased since the breakdown of the Soviet Union (Dubinin et al. 2011, Chapter III), though steppes may now suffer from undergrazing rather than overgrazing (Hankerson et al. 2019). It is important to note that our rewilding index represents a start, but could be expanded to cover these dimensions, for instance by integrating observed or modeled distribution of keystone species (e.g., saiga, Figure SM A-4)), soil carbon dynamics, or fire indicators in order to measure progress towards increasing ecological integrity (Torres et al. 2018).

Our analyses also highlight key areas currently undergoing passive rewilding that may represent target areas for extending the region's protected area network. Existing protected areas are far from each other, as many of them were formed primarily to protect stop-over sites for migratory birds (Schweizer et al. 2014). Most of them are also not strictly protected (though our analyses suggest low human influence inside them; Figure A-4). Expanding the existing protection area network seems particularly useful in the southern part of our study region, where the protection of relatively small areas would provide large benefits in terms of connectivity, while at the same time protecting critical saiga calving grounds (Figure SM A-4) (Singh et al. 2010). Integrating our steppe rewilding index and connectivity analyses with distributional data for species of conservation concern would allow to identify those areas and corridors that would maximize benefit for biodiversity while restoring functional steppes.

However, the window of opportunity to establish such a protected area network may be closing. While human pressure declined drastically across the region, our analyses also show that the recultivation of previously abandoned areas is reverting in parts of the area. These trends appear to spatially coincide with areas highlighted in our analyses as important connectors between protected areas, as well as with key areas of saiga ranges (Figure SM A-4). Reviving the agricultural sector, both in terms of higher crop production and an expansion of the livestock sector, are explicit goals of Kazakhstan's development of the agro-industrial sector (Ministry of Agriculture of the Republic of Kazakhstan 2018). Conservation and land-use planning that seeks to balance conflicts of such land-use trends in areas particularly valuable for rewilding is therefore needed.

At a time when human pressure is increasing in most world regions, making use of rewilding opportunities as they emerge is critical. Grasslands are among the most imperiled biomes of the world (Fuhlendorf et al. 2018), and the substantially reduced human pressure in the Eurasian Steppe after the breakdown of the Soviet Union provides major opportunities for broad-scale steppe restoration. Our analyses highlight how a range of human influence indicators on human influence can be combined to provide a detailed and multidimensional picture of where and why human pressure declines, and where possible rewilding has been taking place – across large areas. This should provide a basis for conservation and land-use planning to make use of opportunities to establish large, connected habitat complexes in the Eurasian Steppe.

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Supplementary Material

Text SM A-1: Mapping cropland abandonment

We mapped cropland abandonment across our study region by classifying Landsat image composites for the years circa 1990 (representing the end of the Soviet era), 2000 (one decade after the beginning of the transition period, representing the time when land-use intensity was lowest), and 2015 (current situation, following a partial revival of the agricultural sector). We produced Landsat image composites, which summarize all the spectral information for a time period of interest and have several advantages over more traditional classifying approaches relying on single Landsat images. Composites provide typically gap-free, wall-to-wall coverage across large study region, composites can be derived specifically for one or several phenologically distinct time points of interest, and provide detailed information via spectrotemproal metrics calculated for all available images (e.g., mean or standard deviation of the reflectance of all cloud-free observations) as well as the meta-information for these images (e.g., the number of cloud-free images used to calculate the metrics).

For this study we calculated three components for each of our three time points (i.e., 1990, 2000, 2015). First, we calculated three so called best-pixel composites centered around the Julian days 121, 180, and 260, representing the best individual observations from the spring, summer and fall of each time point, which is important for mapping cropland-grassland dynamics and farmland abandonment using Landsat imagery (Kuemmerle et al. 2008; Prishchepov et al. 2012). Second, we derived a set of ten spectrotemporal metrics per band (for more details on how these metrics were calculated, see Griffiths et al. (2013)). Third, we derived information on the number of clear-sky observations as well as the zenith and azimuth for each of the best-pixel composites. This resulted in a layer set of overall 85 bands for each of the three time points. All components of all three time points were merged into one multi-temporal stack.

We gathered training data for our classification via on-screen digitization of areas representative for our land-cover classes based on high-resolution imagery from Google Earth, extensive expert-based knowledge from field visits and local collaborators, and the Landsat image composites themselves. The most important classes in this study were “croplands” and “grasslands” and changes between them. An area was defined as cropland in one year, when clear signs of open soil were visible during spring, and a clear vegetation signal during summer. Grasslands were characterized by a clear vegetation signal in spring, summer and fall. Training data were gathered in form of larger polygons to cover the spectral variability within classes.

Once we had collected a sufficient number of polygons for each class, we randomly sampled 5,000 points per class and used this as input for a random forest as classification algorithm. We classified our entire Landsat image composite stack and iteratively gathered more training polygons in areas that were misclassified. Finally, we applied a minimum mapping unit of 10 Landsat pixels (equaling 0.9 ha).

We validated our change map using independent data not used in the classification process. This dataset consisted of 100 randomly sampled points per class , which we labeled it according to our class definition based on visual inspection of the Google Earth imagery and the Landsat composites. We generated an error matrix and calculated overall classification accuracy as well as class-wise user's and producer's accuracies (Foody 2002). We corrected for potential sampling bias and calculated confidence intervals around our error and area estimates (Olofsson et al. 2014). Our maps had an overall accuracy of 86.3%. User's and producer's accuracies were generally high, and highest for the stable classes (e.g. stable cropland with 94.6% and 81.9%).

Text SM A-2: Mapping changes in livestock distribution and human settlements

We modelled landscape connectivity based on circuit flow theory, using Cirtcuitscape 4.0. One common problem of this approach is that current flow between close nodes, protected areas in our case, are disproportionally high (Koen et al. 2014). To circumvent this problem, we assessed landscape connectivity independently from node placement, following the approach outlined by Koen et al. (2014). In this approach nodes are placed randomly in a buffer around the region of interest. Resistance values within the buffer are randomly assigned, but drawn from the distribution of resistance values within the study region. This procedure requires testing two parameters: buffer width and the number of nodes and we followed the general guidance by Koen et al. (2014) and Leonard et al. (2017) to find these parameters. Specifically, we determined the optimal number of nodes by first sampling an initial number of nodes (i.e., 20, (Koen et al. 2014)), then increased the number of nodes by 10, and compared the two current density maps using Pearson's correlation coefficient. If r was below 0.98, we again increased the number of nodes by 10, until the correlation coefficient between the two maps exceeded 0.98 (Leonard et al. 2017). For this study here, the number of nodes at which r saturated was 60.

Once we determined the optimal number of nodes, we identified the optimal buffer width around the study area. Following (Koen et al. 2014), we increased the buffer width in 5% increments of the study area extent, while keeping the number of nodes constant (at 60). Again, we compared current density maps until r>0.98 saturated, which was at a buffer width of 50% of the study area extent.

We then used this parameter combination and calculated landscape connectivity of our study area for both years of interest (i.e., 1990 and 2015). Last, we calculated the differences in landscape connectivity between 2015 and 1990. As we calculated combined human influence across our study region in three ways (i.e., by calculating the product, the maximum, and the mean of our three input layers (percent cropland, distance to livestock stations, distance to settlements)), we calculated current density maps for each of these scenarios.

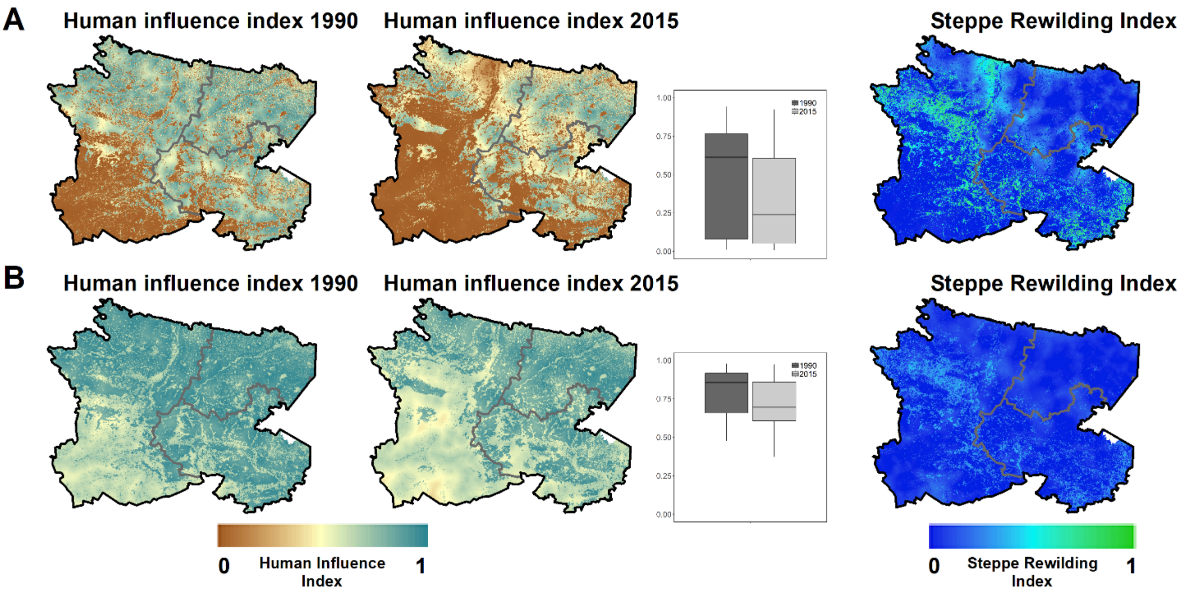

Figure SM A-1: Human influence index and steppe rewilding index in comparison between the two ways of how the three input layers were combined: (A) the product of the three layers; (B) the mean of the three layers.

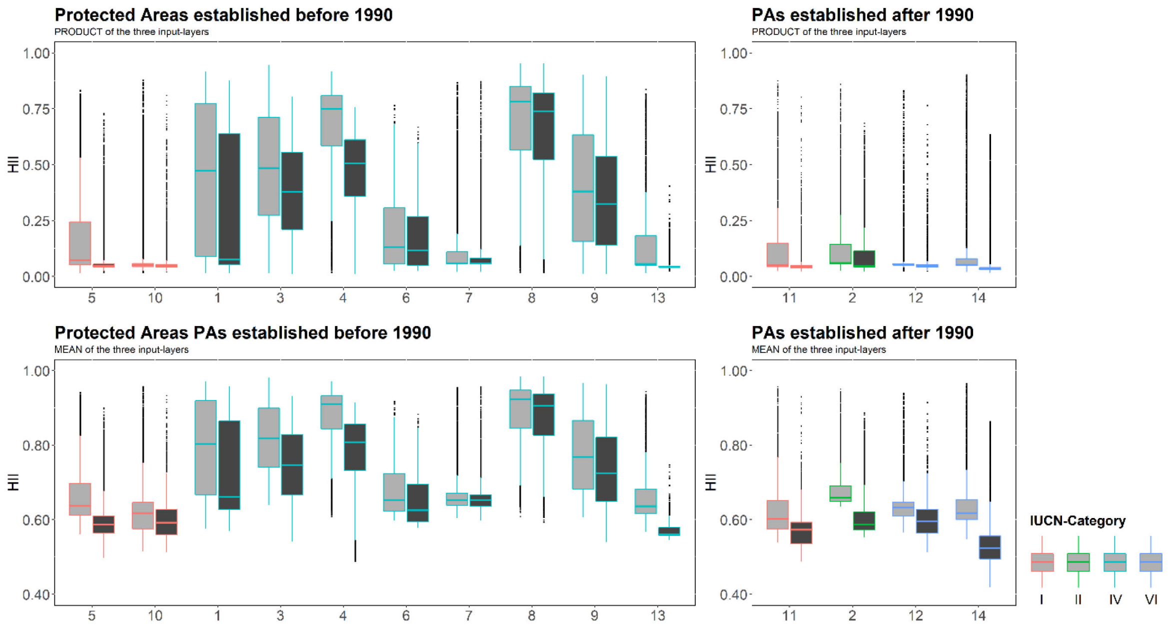

Figure SM A-2: Comparison of human influence values within the protected areas when combining the three input layers through multiplying them (top row) or calculating the average (bottom row).

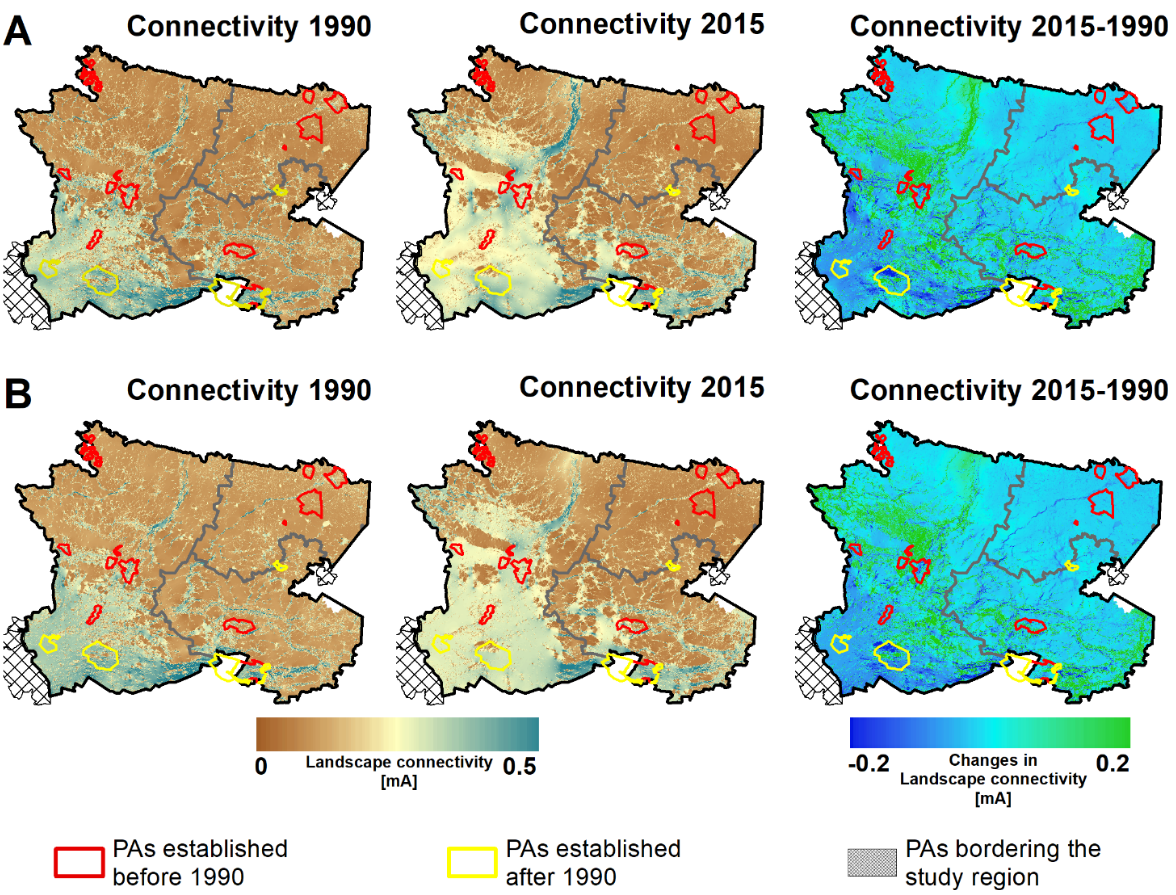

Figure SM A-3: Landscape connectivity compared for the two ways of how the input layers were combined: (A) the PRODUCT of the three layers; (B) the MEAN of the three layers.

Table SM A-1: Protected areas in our study region, and their protection status. The numbering refers to the numbering in figure 3 of the main manuscript.

#	*Protected area name*	*IUCN-Category*
1	Atbasarskii Zakaznik	IV
2	Kokshetau National Park	II
3	Mamlyutskii Zakaznik	IV
4	Mikhailovskii Zakaznik	IV
5	Naurzumskii Gosudarstvennyi Zapovednik	I
6	NN	IV
7	Sarykopinskii Zakaznik (now part of Altyn Dala Gosudarstvennyi prirodnyi reservat)	IV
8	Smirnovskii Zakaznik	IV
9	Sogrovskii Zakaznik	IV
10	Tengiz-Korgalzhynskii Gosudarstvennyi Zapovednik	I
11	Tengiz-Korgalzhynskii Gosudarstvennyi Zapovednik (extension)	I
12	Tosynkumskii (part of Altyn Dala Gosudarstvennyi prirodnyi reservat)	VI
13	Tounsorskii Zakaznik	IV
14	Uly-Zhylanshikskiii (part of Altyn Dala Gosudarstvennyi prirodnyi reservat)	VI

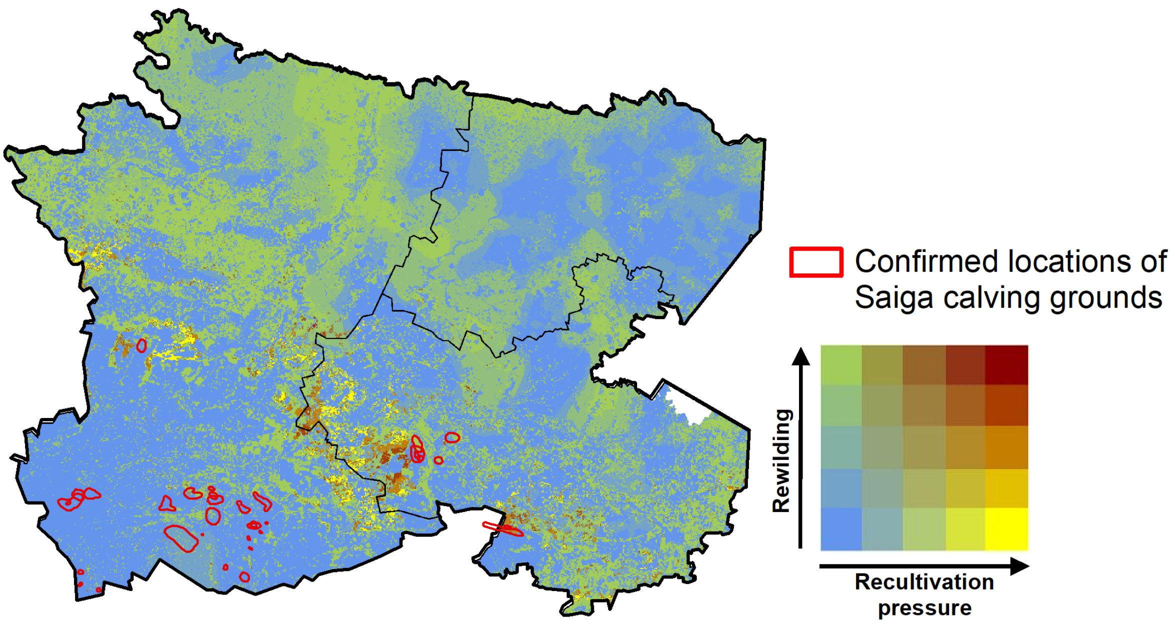

Figure SM A-4: Confirmed locations of Saiga calving grounds, overlaid over our bivariate representation of SRI and recultivation trends. For representation purposes only one version is provided (i.e., the product of the three input layers, see Figure SM A-2 for reference). The calving grounds represent locations that were either directly located in the field, come from aerial surveys or telemetry data. Data source: (Robinson et al. 2017).

Publikationen

PEER-REVIEWED JOURNAL ARTICLES

Published or accepted manuscripts

[5] **Dara, A.**, Baumann, M., Freitag, M., Hölzel, N., Hostert, P., Kamp, J., Mueller, D., Prishchepov, A., & Kuemmerle, T., (2020). Annual Landsat time series reveal post-Soviet changes in grazing pressure. Remote Sensing of Environment.

[4] **Dara, A.**, Baumann, M., Hölzel, N., Hostert, P., Kamp, J., Mueller, D., Ullrich, D., & Kuemmerle, T., (2019). Post-Soviet land-use change affected fire regimes on the Eurasian steppes. Ecosystems.

[3] **Dara, A.**, Baumann, M., Kuemmerle, T., Pflugmacher, D., Rabe, A., Griffiths, P., Hölzel, N., Kamp, J., Freitag, M., & Hostert, P. (2018). Mapping the timing of cropland abandonment and recultivation in northern Kazakhstan using annual Landsat time series. Remote Sensing of Environment, 213, 49-60.

[2] Kauazov, A.M., **Dara, A.S.**, Batyrbayeva, M.Z., Vitkovskaya, I.S., Muratova, N.R., Salnikov, V.G., Turulina, G.K., Polyakova, S.E., Spivak, L.F., & Turebayeva, S.I. (2016). Investigation of timing dynamics of snow cover loss in Northern Kazakhstan. Current problems in remote sensing of the Earth from space, 13, 161–168.

[1] Kraemer, R., Prishchepov, A.V., Müller, D., Kuemmerle, T., Radeloff, V.C., **Dara, A.**, Terekhov, A., & Frühauf, M. (2015). Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan. Environmental Research Letters, 10, 054012.

Submitted manuscripts (in review)

[1] Baumann, M., Bleyhl, B., **Dara, A**., Hölzel, N., Kamp, J., Koshkina, A., Krämer, R., Mueller, D., Pötzschner, F., Prishchepov, A., Schierhorn, F., Urazaliev, R., & Kuemmerle, T., (In review). Declining human pressure and opportunities for rewilding in the steppes of Eurasia. Diversity and Distributions.

CONFERENCE CONTRIBUTIONS

[8] **Dara, A.**, Baumann, M., Kuemmerle, M., Pflugmacher, D., Rabe, A., Griffiths, P., Hölzel, N., Kamp, J., Freitag, M., & Hostert, P. (2018). Revealing spatial and temporal patterns of cropland abandonment and recultivation in northern Kazakhstan after the breakdown of the Soviet Union. Between Europe and Orient. VW Stiftung Status Symposium, Almaty, Kazakhstan. April 2018. *Poster presentation*.

[7] Baumann, M., Bleyhl, B., Kamp, J., **Dara, A.**, Prishchepov, A.V., Krämer, R., Urazaliev, R., Hölzel, N., & Kuemmerle, T. (2018). Cropland abandonment, rewilding and protected area connectivity in the steppes of Kazakhstan. VW Stiftung Status Symposium, Almaty, Kazakhstan. April 2018. *Poster presentation*.

[6] **Dara, A.**, Baumann, M., Kuemmerle, Mueller, D., & Hostert., P. (2016). Mapping cropland abandonment and recultivation in Northern Kazakhstan from 1984 to 2015 using dense Landsat time series. ESA Living Planet Symposium, Prague, Czech Republic. May 2016. *Oral presentation*.

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Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Doktortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Andrey Dara

Berlin, den 15.04.2019